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To my parents

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ABSTRACT

The first essay in this dissertation applies longitudinal data from 1960 to 2014 to study the impacts of the oil price shock in 1973 on mortality rate of the oil producer nations of the Middle East and North Africa. The results show that the increase in oil revenues due to the oil price shock decreased mortality rates including infant mortality rate, under age 5 mortality rate, and adult male and female mortality rates. In addition, we find a negative impact of the oil price shock on economic growth which confirms the findings of the resource curse literature. Also, we find an evidence that as an impact of the oil price shock the number of hospital beds in oil producing nations increased which could explain why a windfall in oil revenues decreased mortality rates. The boom in oil price in 1973 had some impacts on the economy of Indonesia as well. Even though Indonesia is not considered to be one of major oil producers, a significant increase in oil revenues in 1973 enabled the Indonesian governments to invest in central government projects that aimed to improve regional equity in the country. The second essay applies the data from INPRES program, an elementary school construction project that took place in Indonesia between 1973 and 1978, to study the impacts of an exogenous variation in number of years of schooling on fluid intelligence measured by Raven test scores. We combine INPRES data with the Indonesian Family Life Survey (IFLS) which contains individual cognitive ability tests. The results show that the program had positive and significant impacts on years of schooling and fluid intelligence. Also, we find positive impacts of schooling on cognitive abilities. Besides cognitive abilities that are crucial to perform any task, non-cognitive abilities are just as important for the humans to function and be productive. In the third essay, we use exogenous variation in student aid eligibility in 1982 that took place in the United States to study the impact of schooling on non-cognitive skills. Following Heckman (2006) we apply Rosenberg Self-Esteem Scores and the Rotter Locus of Control Scale from NLSY79 dataset as measurements of non-cognitive skills. Our results suggest that schooling has a positive impact on non-cognitive abilities such that it increases internal locus of control and it improves self-esteem.

CONTENTS

ACKNOWLEDGMENTS iii
ABSTRACT iv
CHAPTER 1 Oil and Mortality 1
1.1 Introduction 1
1.2 Empirical Design 8
1.3 Data and Treatment Assignment 10
1.4 Empirical Results 18
1.4.1 Difference-In-Differences 18
1.4.2 Robustness Check 21
1.4.3 Impact on Hospital Beds 24
1.4.4 Event Studies 25
1.4.5 Obtaining Stationary Residuals 27
1.5 Conclusion 28
CHAPTER 2 Schooling and Fluid Intelligence 30
2.1 Introduction 30
2.2 Data and Identification Strategy 36
2.2.1 Sekolah Dasar INPRES Program 36
2.2.2 Indonesia Family Life Survey (IFLS) 37
2.2.3 Identification Strategy 38
2.3 Empirical Design 39
2.4 Empirical Results 40
2.4.1 Effect on Education 40
2.4.2 Effect on Fluid Intelligence 51
2.4.3 Two-Stage Least-Squares Estimates 58
2.5 Conclusion 62
CHAPTER 3 Does Schooling Causally Impact Non-cognitive Skills? 65
3.1 Introduction 65
3.2 Data and Identification Strategy 72
3.2.1 Data 72
3.2.2 Identification Strategy 73
3.3 Empirical Design 75
3.4 Empirical Results 76

3.5 Conclusion 85
APPENDICES **88**
APPENDIX A 88
APPENDIX B 89
APPENDIX C 90
APPENDIX D 91
APPENDIX E 95
APPENDIX F 97
APPENDIX G 99
APPENDIX H 103
BIBLIOGRAPHY **107**

LIST OF TABLES

Table 1. Summary statistics 16
Table 2. Summary statistics treated versus control group before and after the event 18
Table 3. Difference-in-differences results 20
Table 4. Robustness check; difference-in-differences estimations. 1960-1978 22
Table 5. Robustness Check; difference-in-differences estimations. Event year 1970 23
Table 6. difference-in-differences estimations: impacts of the oil price shock on hospital beds 25
Table 7. Event study estimations 27
Table 8. Fisher-type unit-root test based on Augmented Dickey-Fuller test 28
Table 9. The Impacts of the School Construction Program on Years of Education: Basic Results 41
Table 10. The Impacts of the School Construction Program on Years of Education: Reduced-Form Evidence 44
Table 11. Impacts of the School Construction Program on Years of Education: Restricted Estimations 46
Table 12. The Impacts of the School Construction Program on Levels of Education 49
Table 13. The Impacts of the School Construction Program on Education: By Gender 50
Table 14. The Impacts of the School Construction Program on Raven Test Scores: Basic Results 52
Table 15. Impact of the School Construction Program on Fluid Intelligence: Reduced-Form Evidence 56
Table 16. Impact of the School Construction Program on Fluid Intelligence: Restricted Estimations 58
Table 17. The Impact of Years of Education on Fluid Intelligence: Least Square Estimations 60
Table 18. Impact of Years of Education on Fluid Intelligence: Two-Stage Least-Square Estimations 61
Table 19. Impact of Years of Education on Fluid Intelligence by gender: Two-Stage Least-Square Estimations 62
Table 20. Characteristics of NLSY79 dataset 72
Table 21. NLSY Summary Statistics 75
Table 22. Impact of eligibility for Social Security student benefits on education 77
Table 23. Impact of education on non-cognitive skills – least-square estimations. Independent variable of interest: schooling by age 23 81
Table 24. Impact of education on non-cognitive skills – least-square estimations. Independent variable of interest: complete college by age 23 82
Table 25. Impact of education on non-cognitive skills – two-stage least-square estimations. Instrumented variable: schooling by age 23 84
Table 26. Impact of education on non-cognitive skills – two-stage least-square estimations. Instrumented variable: complete any years of college by age 23 84
Table 27. Rosenberg Self-Esteem Scale questions in NLSY1979 database 95
Table 28. Data on Rosenberg Self-Esteem Scale respondents 1987 95
Table 29. Respondents in 1987 interview along with their associated Rosenberg Self-Esteem Scale scores 96
Table 30. Data on Rosenberg Self-Esteem Scale respondents 2006 96
Table 31. Respondents in 2006 interview along with their associated Rosenberg Self-Esteem Scale scores 96
Table 32. Rotter Locus of Control Scale questions in NLSY1979 database 97
Table 33. Data on Rotter Locus of Control respondents 2014 98
Table 34. Data on Locus of Control respondents 2014: pair B 98
Table 35. Rotter Locus of Control Scale respondents in 2014 interview along with their associated scores 98
Table 36. Impact of eligibility for Social Security student benefits on years of schooling by age 23 100

Table 37. Impact of eligibility for Social Security student benefits on complete any years of college by age 23 ... 101
Table 38. Impact of eligibility for Social Security student benefits on complete any years of college by age 28 ... 102
Table 39. Impact of education on Rosenberg Self-Esteem 1987– two-stage least-square estimations. Instrumented variable: schooling by age 23 ... 103
Table 40. Impact of education on Rosenberg Self-Esteem 2006– two-stage least-square estimations. Instrumented variable: schooling by age 23 ... 104
Table 41. Impact of education on Rotter Locus of Control 2014– two-stage least-square estimations. Instrumented variable: schooling by age 23 ... 104
Table 42. Impact of education on Rosenberg Self-Esteem 1987– two-stage least-square estimations. Instrumented variable: complete any years of college by age 23 ... 105
Table 43. Impact of education on Rosenberg Self-Esteem 2006– two-stage least-square estimations. Instrumented variable: complete any years of college by age 23 ... 105
Table 44. Impact of education Rotter Locus of Control 2014– two-stage least-square estimations. Instrumented variable: complete any years of college by age 23 ... 106

LIST OF FIGURES

Figure 1. The global oil price trend ... 12
Figure 2. A. Daily oil income of the treated countries in million U.S. dollars. B. Daily oil income per capita in the treated countries in U.S dollars. ... 13
Figure 3. Daily oil production of the treated countries- million barrels ... 14
Figure 4. Mortality rates ... 17
Figure 5. Event studies ... 26
Figure 6. Ratio of the INPRES schools constructed each year ... 37
Figure 7. Impacts of the School Construction Program on Years of Education: Reduced-Form Evidence 43
Figure 8. The impact of the program on levels of education ... 48
Figure 9. Impacts of the School Construction Program on Raven test score: Reduced-Form Evidence ... 54
Figure 10. Impacts of the School Construction Program on Raven test score: Reduced-Form Evidence .. 55
Figure 11. Number of hospital beds per head in each treated country ... 88
Figure 12. Dorsolateral prefrontal cortex, anterior cingulate cortex, and the hippocampus ... 89
Figure 13. Indonesian Family Life Survey (IFLS) on map of Indonesia ... 90
Figure 14. Intensity of the INPRES program from 1973-1978 on map of Indonesia ... 90

CHAPTER 1

OIL AND MORTALITY

1.1 Introduction

An irony of our world is that the countries that are blessed with an easy income from natural resources usually are not blessed with higher welfare. This fact raises the question of how the welfare level of the resource rich nations would have been different if they had never had those resources. Would they enjoy higher levels of health and life expectancy, or would they just be similar to many other nations that never have been resource rich? In this chapter we attempt to shed light on the impacts of oil revenues on mortality rate in major oil producer nations applying an exogenous oil price shock in 1973. We use longitudinal data from 1960 to 2014 and we apply difference-in-differences approach to investigate the main question of the research. Our findings show that the oil price shock did not lead to higher GDP per capita, but it did lead to lower mortality. A possible explanation is that the oil price shock allowed for higher spending on publicly funded health care. We find a positive impact of the oil price increase on the number of hospital beds which suggests that higher oil revenues increased spending on public health and that possibly decreased mortality.

The story goes back to the attempts of the Shah[1] of Iran to increase the price of oil in the 1970s. Iran was a major producer of oil in those days. Hence, it possessed a significant amount of power in OPEC. The Shah's attempts to increase oil prices goes back to 1971 which he successfully increased the oil price from \$1.64 to \$4.1 in a three-years period. However, the real shock came in 1973 when the prices skyrocketed. In December 1973 the Shah forced OPEC[2] members to increase the price of crude oil more than three hundred percent. The global price of crude oil which was \$4.1 in December 1973 increased to \$13.0 in January 1974. The documents, including a partially declassified CIA report entitled, *Shah of Iran Culprit in High Oil Prices*, show that the Shah, was the key person that can be blamed for the oil price shock of 1973-1974. Despite the fact that the OPEC members should agree on the oil price policies, the other OPEC members

[1] Mohammad Reza Shah Pahlavi, King of Iran from 1941 until 1979.
[2] The Organization of the Petroleum Exporting Countries (OPEC) is an organization of some major oil suppliers that acts like a cartel to control the global price of oil.

were not happy with the Iran's attempt for increasing the oil price. Saudi Arabia, another major oil producer and powerful member of OPEC tried to stop Iran from raising the prices. The Shah, who thought the oil reservoirs of Iran would be depleted before year 2000, tried to industrialize Iran as fast as possible to eradicate poverty. The Shah of Iran dreamed about bringing back the great Persian civilization[3], and needed money to fund his dream. The following quote by Garavini, G. (2011) explains why the Shah was interested in increasing the prices:

> *"During period of high production, Shah hopes to see Iran transformed into an industrial power comparable with France or West Germany. Needs high prices and high production rates to see Iran make such great strides during lifetime. Therefore, his insistence on huge price hikes and refusal to cut back production" (p. 481).*

Painter (2014) argues that in the late 1960s the British wanted to withdraw their military forces from the Persian Gulf in the south of Iran. Therefore, the United States, busy with the Vietnam war, turned to Iran to serve as the Guardian of the Persian Gulf. The Shah of Iran eagerly accepted to be the guardian of the Persian Gulf because he was trying to establish the power of ancient Persia once again. In 1972, the Nixon administration agreed to sell any weapons except nuclear weapons to Iran. Between 1970 and 1978 Iran purchased over 20 billion dollars worth of weapons and other military equipment from the US. Painter maintains that "higher [oil] prices allowed Iran to increase its military spending and replace Great Britain as the "guardian of the gulf." (p. 197).

Why it matters to study the impacts of oil revenues on mortality? One reason is that the impacts of oil revenues on mortality is neglected in the literature. A large literature studies the impacts of income from natural resources on economic growth which of course is important, but the problem is that economic growth solely is an imperfect proxy for welfare. In a highly unequal society that a small percentage of the population controls most of the wealth of the nation, economic growth could be noticeably high. Unlike economic growth, mortality could be highly informative about the impacts of an event such as an increase in oil revenues on the well-being of the whole population. Oil revenues could bring large amounts of income to a country. If this income is invested on hospitals and other health relevant factors, even in the short term, it can have a significant impact on reducing child mortality. The public sector often plays a very important

[3] He even published a book in 1978 entitled *Toward the Great Civilization*

role in health care. Perhaps higher oil revenues for the public sector facilitate more spending on health care. Another reason is that, it is intrinsically valuable to understand the factors that save human life and decrease mortality.

Preston[4] (2007) might be the most influential study that investigates the connection between income and mortality. He argues, besides an improvement in health services such as an increase in quality and quantity of the hospitals and clinics, a higher level of wealth helps a society to afford more nutritious and healthier food, leisure, education, etc. that might indirectly affect mortality rates. He finds an association between national income per head and life expectancy for 1900s, 1930s, and 1960s. Also, he has some other important findings. First, income per capita has a non-linear, positive effect on life expectancy. The effect attenuates as countries become richer. Second, the relationship has shifted upward over time. Third "Factors exogenous to a nation's level of income per head have had a major effect on mortality trends in more developed as well as in less developed countries" (p. 489). He explains that income levels per se accounts for 10 to 20 percent growth in life expectancy in the world and factors exogenous to a country's current level of income account for 75 to 90 percent. He argues that association between national income and life expectancy is indirect and if higher national income goes to public health, nutrition, education, etc. then it can decrease mortality and improve life expectancy:

> *There is no reason to expect a direct influence of national income per head on mortality; it measures simply the rate of entry of new goods and services into the household and business sectors. Its influence is indirect; a higher income implies and facilitates, though it does not necessarily entail, larger real consumption of items affecting health, such as food, housing, medical and public health services, education, leisure, health-related research and, on the negative side, automobiles, cigarettes, animal fats and physical inertia (p. 484.)*

There has been debates on the relative importance of the mentioned factors above. While Preston (2007) and Deaton (2006) emphasize the roles of public health measures, Fogel (2004) puts more weight on the of impacts of rising income on nutrition. In addition to Preston (2007), Kitagawa and Philip (1973), Cutler et al. (2006), Cristia (2007), Mackenbach et al. (2008), Duggan

[4] Preston published the first version of his paper in 1975

(2008); Braveman et al. (2010), Waldron (2013), Chetty et al. (2016) have found that a greater wealth does lead to a lower mortality and higher life expectancy. However, not every study finds a significant effect of income on mortality reduction. At least two studies including Stolnitz (1965) and Demeny (1965) find no significant relationship between income per capita and mortality.

The impacts of oil price shocks on different aspects of an economy have been widely discussed in the literature (see e.g. Park and Ratti, 2008; Jimenez-Rodriguez, 2008; Farzanegan and Markwardt, 2009; Iwayemi and Fowowe, 2011; Aydın and Acar, 2011; Scholtens and Yurtsever, 2012; Cunado and de Gracia, 2014; Gao et al., 2014; Kang et al., 2014; Zhang and Qu, 2015; Tsai, 2015; Cunado et al., 2015; Ju et al., 2016; Zhang and Tu, 2016; Nusair, 2016; Zhao, 2016; Kim et al., 2017; Cross and Nguyen, 2017; Lee et al., 2017; Karnizova and Reza, 2018; Moshiri and Moghaddam, 2018; Nasir et al., 2018; Ioannidis and Ka, 2018; Oladosu et al., 2018; Lorusso and Pieroni, 2018; Tchatoka et al., 2018; Herrera et al., 2019; Lee and Lee, 2019; Nusair and Olson, 2019; Grigoli, et al., 2019; Bergmann, 2019). However, the mentioned studies are different from our paper because what they consider as oil price shocks is not a same concept as what we refer to as the 1973 oil price shock. The oil price shocks in the mentioned studies mostly refer to oil price volatilities or oil price uncertainties. However, in our paper we focus on the oil price increase in 1973 as an exogenous variation in oil price to study the impacts of oil revenues on mortality in oil producing nations. In addition, the impacts of oil price change or oil price shocks on welfare and economies of the oil producing nations has not received attention in the literature and most of the studies focus on the economies of the large oil consumers such as the United States and China.

Note that, as the results of this paper confirms, the oil price shock in 1973 had a negative and significant impact on mortality rate (i.e. decreased mortality) and at the same time led to a lower rate of per capita economic growth. The reasons why oil revenues might negatively affect economic growth has been discussed in the Resource Curse literature. The Resource Curse literature mostly argues that natural resource discoveries decrease economic growth and income per capita (see e.g. Sachs and Warner, 1995; Velasco, 1997; Gylfason et al., 1999; Tornell and Lane, 1999; Leite and Weidmann, 1999; Ross, 2001; Papyrakis and Gerlagh, 2007; Caselli and Cunningham, 2009; Brollo et al., 2010; Vicente, 2010; Van der Ploeg, 2011; Sala-i Martin and Subramanian, 2013). Resource curse studies argue that due to reasons such as Dutch Disease, corruption, weakening the institutions, etc. income from natural resources has an adverse impact on economic growth. For example, Papyrakis and Gerlagh (2007) argue that abundance of natural resources increases corruption and decreases R&D expenditure, openness, schooling, and investment. Also, they maintain that in more volatile economies with poor financial systems, high corruption, lack of rule of law, and political issues the mentioned problems could be more severe. Also, other studies show natural resource windfalls might decrease investment and openness and have negative effects on schooling and economic growth (Papyrakis and Gerlagh, 2007).

One explanation for resource curse relates to change in incentives or behavior of the politicians. Caselli and Cunningham (2009) argue that income from natural resources can alter the incentives of the leaders and make them act in an opposite direction of well-being of their societies. Also, Velasco (1997) and Tornell and Lane (1999) maintain that a windfall of natural resources can have adverse effects on economies through political processes such as increased in rent-seeking. In addition, other studies of the resource curse literature emphasize an increase in corruption and a decrease in the quality of the politicians because of natural resource abundance (Brollo et al. 2010; Vicente 2010).

Another explanation for a negative impact of natural resource discoveries on economic growth is “Dutch Disease” which argues that the export of natural resources tends to increase exchange rates and hence diminishes the competitiveness of industrial exports (see e.g. Corden 1982; Corden and Neary,1984; Sachs and Warner, 1995; Gylfason et al., 1999; Van der Ploeg, 2011; Sala-i Martin and Subramanian, 2013).

In this paper we find negative impacts of the oil price shock of 1973 on GDP per capita as well as on mortality. Also, we find positive impacts of the oil price shock on hospital beds. Therefore, it seems that spending on public health has been increased after increase in price of oil. Because health sector is considered as a services sector Dutch Disease can provide one explanation for our results. Dutch Disease is hypothesized by Corden (1982) and Corden and Neary (1984). Dutch Disease hypothesizes that an exogenous shock in oil price increases the real exchange rate which results in decline in production of the agriculture and manufacturing sectors and increases the production of the services sector.

In Dutch Disease hypothesis the whole economy is divided to the sectors that produce tradable and non-tradable outputs. The tradable sectors include booming sector (oil) and lagging sector (agriculture and manufacturing). The non-tradable sector only includes services sector. The tradable sector is subject to global competition and the price of the outputs of the tradable sector (oil, manufacturing, and agriculture) are determined abroad by the global supply and demand functions. However, the price of the outputs of non-tradable sector (services) is not subject to global competition.

Corden and Neary (1984), differentiate a *resource movement effect* from a *spending effect*. The resource movement effect occurs in a condition that the supply of oil is not perfectly inelastic and an increase in global price of oil shifts up the demand for capital and labor in the oil (booming) sector. This will lead to larger return to capital and higher wages in the booming sector. In a condition that production factors are mobile this will cause a shift of capital and labor from services and lagging sectors (i.e. agriculture and manufacturing) to the booming sector (i.e. the oil sector)). The employment and output in the booming sector increase, while employment and output in lagging and services sectors decline. Decline in output of the lagging sectors is referred to as "direct de-industrialization." The price of lagging sector outputs is determined abroad and therefore remains unchanged. Fall in the production of services causes excess demand and hence a rise in the price of services. Therefore, the price of non-tradable products relative to the price of tradable products increases which leads to an increase in real exchange rate.

Usually the resource movement effect does not happen because the number of workers in the booming sector is low comparing to the whole economy. Nevertheless, the spending effect is likely to occur.

The spending effect takes place because a raise in oil prices increases profits and wages in the oil sector which improves the aggregate demand in the whole economy. This does not affect the prices of manufacturing goods and oil since their prices are determined abroad by the global supply and demand functions, but prices of services increase. This again results in an increase in real exchange rate. The increase in price of services occurs because the rise in aggregate demand in the whole economy transfers to the services sector as well.

If labor is mobile between the tradable and services sectors, an increase in the demand for services will lead to an upward shift in the supply of services. Also demand for labor and therefore wages in the services sector increase.

This will encourage workers to move from the tradable sector (i.e. oil and manufacturing) to the services sector and pushes the tradable sectors to increase their wages. However, they cannot compete and their profits fall. The resulting drop in employment and outputs of booming and lagging sectors is referred to as "indirect de-industrialization." by Corden and Neary (1984).

Combining the two effects, the Dutch Disease hypothesis generates some important predictions. One, there is an unambiguous decrease in production and employment in the manufacturing sector. Second, because the resource movement effect and the spending effect pull in opposite ways the overall effect on employment and production of the services and oil sectors is ambiguous. Nevertheless, if the oil sector employs a low ratio of workers of the whole economy, then the spending effect dominates the resource movement effect. This leads to increase in output and employment of services sector. In practice it has been shown that the spending effect dominates the resource movement effect (Oomes and Kalcheva, 2007; Hasanov, 2013).

The mechanisms and the literatures discussed previously in this section provide some insights about the plausible impacts of the oil price shock of 1973 on mortality, and economic growth of the oil producer countries. To the best of our knowledge a similar study has not been done before. Therefore, this empirical study attempts to fill this gap in the literature. For reasons that are discussed in the Empirical Design section of the paper, difference-in-differences fixed effect models are applied to investigate the main question of the research.

The key findings of this research can be summarized as follow:

a. The oil price increase of 1973 decreased mortality rates including infant mortality rate, mortality under age 5, adult female mortality rate, and adult male mortality rate in the oil producing nations of the Middle East and North Africa.
b. Another impact of the oil price shock is that it decreased GDP per capita. This result confirms the findings of the resource curse literature.
c. Yet another finding is the positive impact of the oil price shock on the number of hospital beds. This finding suggests that the oil producing nations improved their investments in health care after the windfall of oil revenue from the oil price shock.

In the discussion section we argue that the results of this paper could be perfectly be explained by Dutch Disease hypothesis. Yet, another explanation why hospital beds and mortality rates have improved despite the negative impact of the oil price shock on economic growth relates to the behavior and incentives of the politicians. Due to failure of the politicians in preventing resource curse they might try to invest on visible projects to people that may improve their popularity. Investing in health care such as building hospitals are visible to citizens and therefore might help the politicians to stay in power longer.

The rest of this paper is organized as follow. Section 2 outlines the empirical design of the research. Section 3 explains the Data and treatment assignment. Section 4 provides the results and section 5 presents the conclusion of the study.

1.2 Empirical Design

Since the price shock was managed by the Iranian king, the increase in oil prices could be an endogenous variable for the Iranian economy. Nevertheless, it's unlikely that the price shock in 1973 was an endogenous variable for the economy of other oil producer nations. The oil price increased based on the decision of a person outside their country without them having a significant impact on the process. Hence the oil price shock of 1973-1974 is an exogenous variable for other nations, if not for Iran, and in this paper, we apply that to study the impacts of oil revenues on mortality in oil producing nations. The CIA report suggests that perhaps Venezuela was a supporter of Shah's decision. For this reason and other reasons that will be discussed later in the paper, Venezuela is not included in this paper. Hence, there is no concern about possible endogeneity of oil price increase in Venezuela's economy.

In this paper difference-in-differences (DID) approach has been applied to investigate the impacts of the oil price shock in 1973 on mortality rates. Also, we apply the same approach to estimate the impact of the oil shock on economic growth and hospital beds. Difference-in-differences (DID) approach estimates the impact of an event on an outcome variable by comparing the average change in the outcome variable for the treatment unit and the average change for the control group over time. We apply this approach because it provides a nice framework to investigate the impact of an event (an increase in oil price) on an outcome variable (mortality, for example). Card and Krueger (1994) might be the most famous study that used the difference-in-differences approach. They investigated the impacts of an increase in minimum wages (an event) on employment (an outcome variable) at fast food industry in New Jersey and Pennsylvania.

Before applying DID, we divide the countries in two groups. One is the treatment group and the other is the control group. A treatment unit, which is a country in the treatment group, is one of major oil producer nations. And the control countries are nations that do not produce oil in the same region (i.e. the Middle East and North Africa) with the treated countries.

We apply the following model to estimate the average effect of the treatment on the outcome variables:

$$Y_{ct} = \beta_1 + \beta_2 Post_t + \beta_3 Treat_c + \beta_4 Treat_c * Post_t + \alpha_c + \gamma_t + \epsilon_{ct} \tag{1}$$

where Y_{ct} is the outcome variable in country c and year t. $Post_t$ is an indicator which takes value one if $t>T_0$ where T_0 is the event year (i.e. 1973). $Post_t$ is zero for the years before the event. $Treat_c$ is an indicator that takes a value one if a country is treated (i.e. it is an oil-producing country). $Treat_c$ takes a value zero if a country is not treated (i.e. it is not an oil-producing country and it is one of the countries in the control group). α_c is country fixed effect. γ_t is year fixed effect dummies for year t. This variable controls for the common shocks experienced across the region.

A key assumption of the difference-in-differences model is the common trend assumption. In fact, the identification in the difference-in-differences models relies on the common trends (parallel trends) assumption that requires the dependent variable for the treatment unit and the control group have the same trends. If the two groups have the same trend, then the differences should be due to the treatment.

The common trend assumption is not easy to verify. However, one can show that the outcome variable in the control and treatment groups are parallel before the treatment. Even if the pretreatment trends are parallel, changing policies and conditions after the treatment could affect the results. In this paper, the outcome variable which is Y_{ct} should be parallel for the treated countries and control group before the treatment. During the post treatment period, based on the mentioned assumption, if there was not a treatment, the outcome variable should be parallel in the treated and the control units. To meet the mentioned assumption, we limit this research to the Middle Eastern and North African countries. Some sub-Saharan African countries such as Nigeria are among major oil producers, but experienced high death rates in 1980s and 1990s because of reasons unrelated to oil revenues. Thus, for them the parallel trend assumption does not hold and they are not included in the analysis. In addition, Venezuela is one of top oil producing counties in Latin America, but again because the parallel trend assumption was not satisfied it is not included in the paper. Including the industrial European countries such as Norway which is among major oil producer nations violates the same assumption. The reason is that timing, pace, and level of industrialization among European countries that would create a control group for Norway significantly vary which makes it difficult to capture the impacts of oil revenues on mortality in Norway relative to its potential counterfactual. In other words, since the European nations have begun to industrialize not at the same time and same level, β_4 in equation 1 might get affected by timing and pace of industrialization of the treated and control countries and fail to show an unbiased impact of the oil price shock on mortality.

1.3 Data and Treatment Assignment

The source of oil production data is International Petroleum Encyclopedia. The source of GDP per capita is Maddison Project Database (MPD). Also, the global oil prices are taken from The World Bank Commodity Price Data. The source of the rest of the data is the World Bank.

The oil-producing countries that are considered as treated countries in this paper include Algeria, Bahrain, Iran, Iraq, Kuwait, Libya, Oman, Qatar, Saudi Arabia, Syria, Yemen, and United Arab Emirates. Also, the control group which are some other countries in the Middle East and North Africa (i.e. same region as the treated group) include Djibouti, Israel, Jordan, Lebanon, Morocco, Tunisia, Turkey. Because of possibility of endogeneity of the oil shock for the Iranian economy in some of the regressions Iran is excluded.

Figure 1 and shows the global price of oil from 1960 to 2005. The oil price shock in 1973 is charted using a dashed red line. Until the 1970s the price of oil was low for decades. As can be seen in Figure 1 from 1960 to 1970 the price of oil actually decreased a few cents each year. The oil price which was 1.63 U.S. dollars in 1960, over a decade, decreased to 1.21 U.S. dollars in 1970. However, after the Shah's pressure on the Seven Sisters[5], an oligopoly that dominated the oil reserves and controlled the price of oil for decades, the price started increasing in the 1970s. In

[5] Seven Sisters is a term for an oligopoly consisted of seven transnational oil companies of the "Consortium for Iran". The seven sisters include: 1. Anglo-Iranian (started as Anglo-Persian Oil Company. Now British Petroleum). 2. Standard Oil Company of California (Now Chevron). 3. Gulf Oil (later part of Chevron). 4. Royal Dutch Shell. 5. Standard Oil Company of New Jersey (Esso, later Exxon, now part of ExxonMobil). 6. Standard Oil Company of New York (Socony, later Mobil, now part of ExxonMobil). 7. Texaco

1970 the Shah of Iran threatened the Seven Sisters that if they didn't consider the wish of the OPEC members in production/price negotiations, the OPEC members would change their policy and they would decide about oil prices themselves. After this event the Seven Sisters agreed to increase the price of oil to adjust for inflation of both producer and consumer countries. Hence the global price of oil increased from 1.21 U.S. dollars in December 1970 to 1.64 U.S. dollars in January 1971. Again, in July of 1971 the price of oil increased by 10 cents from 1.64 U.S. dollars to 1.74 U.S. dollars.

Every 6 months, from middle of 1971 until May 1973, the price of oil increased by 10 cents. However, in July 1973 it increased by 35 cents from 2.35 to 2.7 U.S. dollars. In October of the same year the price increased from 2.7 to 4.1 U.S. dollars.

However, comparing to price shock of December 1973-Jannuary 1974, the price increase of October 1973 is relatively moderate. In December 1973, the OPEC members had a meeting in Isfahan, Iran. Jamshid Amouzegar was Iran's representative in the meeting. He was asked by the Shah to use Iran's power in OPEC for a significant increase in oil price. However, even before the OPEC meeting was finished, the Shah of Iran announced that oil price has been raised in the OPEC meeting. The new global price of oil in January 1974 was $13.0 U.S. dollars.

Note, that the price of oil increased again in 1979, but after a few years it came down and for over two decades stayed almost at the same level that it was in 1974. Again, Iran had a big role in price increase of 1979. In February 1979 Islamic Revolution happened in Iran and Shah lost his power. For a few years prior to 1979, Iran was one of the largest oil producers on Earth. However, over the same period, demonstrations against Shah were on rise. In 1978 and 1979 the workers of oil industry in Iran joined the demonstrators and stopped going to work. Therefore, the oil industry in Iran stopped functioning and oil production decreased significantly which was followed by an increase in oil price.

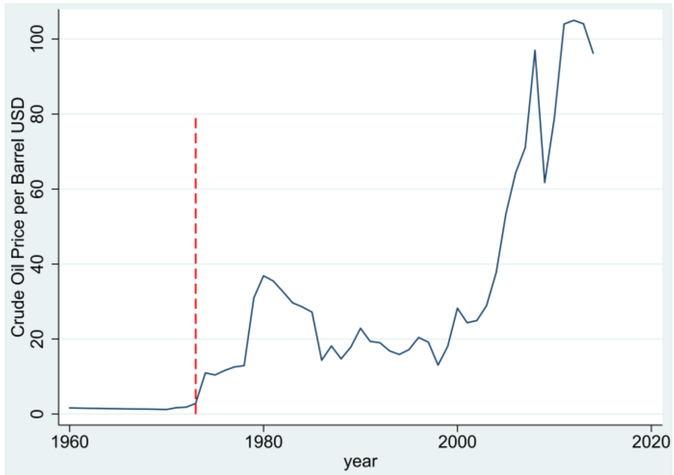
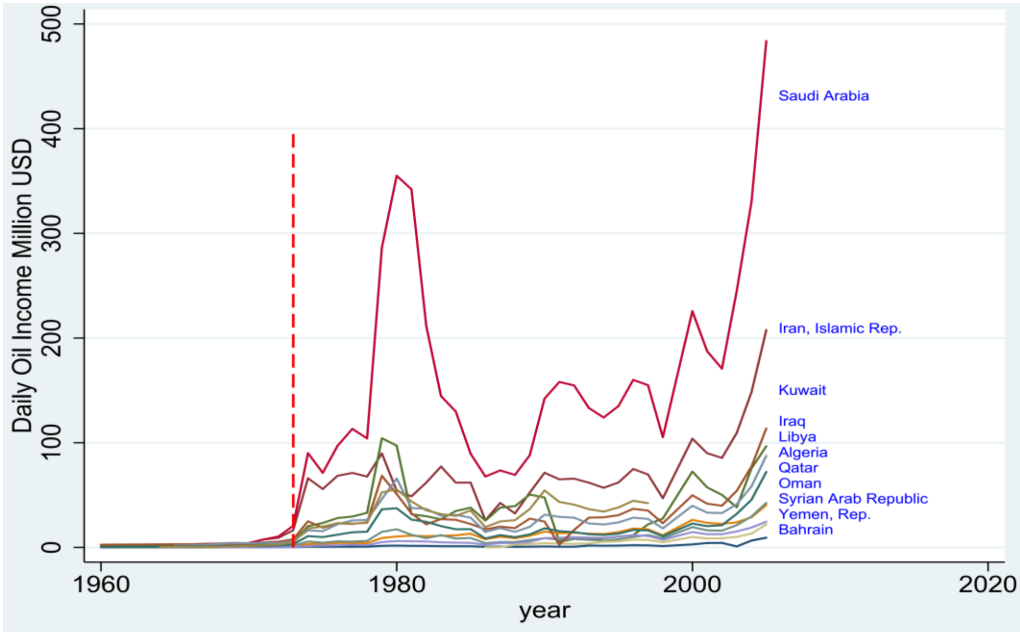


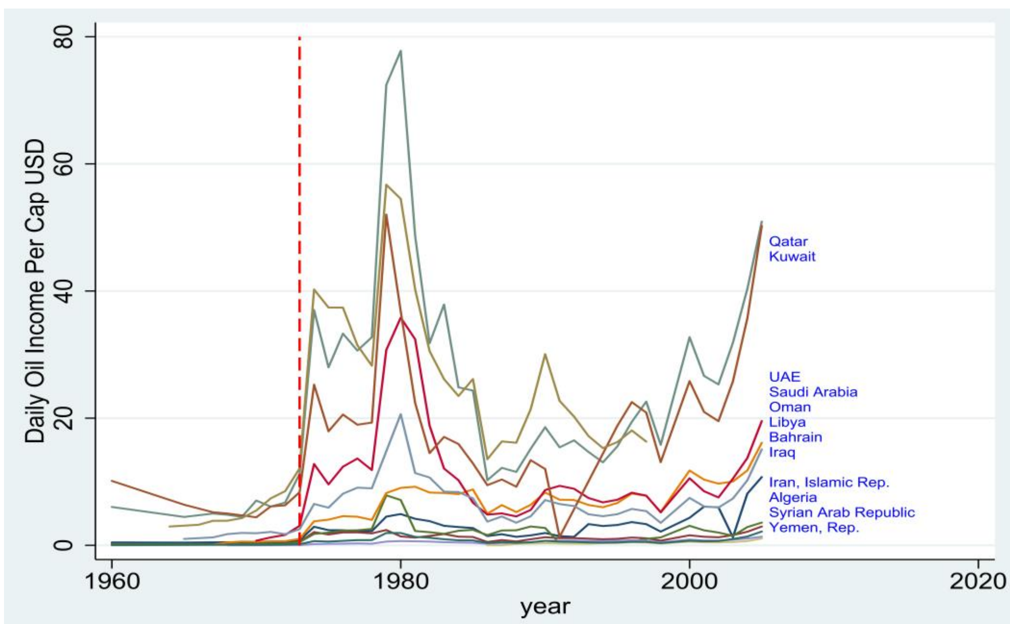
Figure 1. The global oil price trend

Another important event that must be considered is the famous “Embargo". The oil embargo began in October 1973 when Arab Nations decided to decrease their oil exports to nations they believed to be supporters of Israel. Some of targeted countries include Canada, Japan, the Netherlands, the United Kingdom, the United States, and Portugal. When the oil embargo started in October 1973, the price of oil was less than 3.0 U.S. dollars, but when it ended in March 1974 the price was 13.0 U.S. dollars. Because the oil embargo and price shock of 1973-1974 coincided many believed that oil embargo caused the price increase, but as discussed above in fact Shah of Iran was behind the price increase. The western media constantly blamed the Shah for the price increase of 1973-1974.

After 1973 the oil income of the oil producing nations significantly increased. Figure 2.A shows daily oil revenue of the oil producing nations (i.e. the treated countries) in million U.S. dollars. As the figure shows, the real increase in oil income started in January 1974 and among Middle Eastern and North African countries, Saudi Arabia and Iran earned the highest oil incomes after the price increase. Figure 2.B represents daily oil income per capita of the treated countries in U.S dollars. As with daily oil income, daily oil income per head drastically increased after 1973. Qatar, Kuwait, and United Arab Emirates that have smaller populations earned the highest levels of oil revenue per head. The most striking feature of Figure 2.A and 2.B is the large increase in the oil income of the treated countries after 1973.



A.



B.

Figure 2. A**. Daily oil income of the treated countries in million U.S. dollars.** B**. Daily oil income per capita in the treated countries in U.S dollars.**

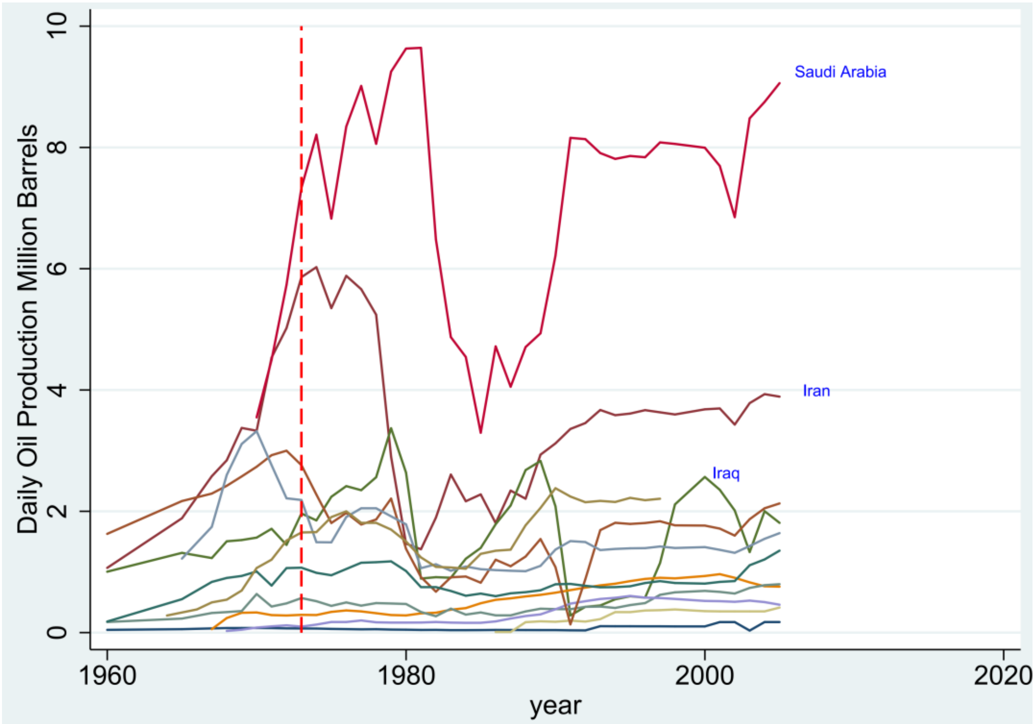


Figure 3. Daily oil production of the treated countries- million barrels

Figure 3 shows the oil production level of the treated countries in million barrels. Saudi Arabia and Iran that significantly increased their production level in the early 1970s, kept increasing it until 1975. In 1975 they both decreased their production levels to some extent which is much less than their increase in production from 1970 until 1975. Usually, the rest of the countries have been producing less oil than Saudi Arabia and Iran.

The summary statistics of the main variables of the study are represented in Table 1 In each cell three numbers are provided. The first number on top is the mean of each variable over the research period which is from 1960 to 2005. The second number in each cell which is provided in parentheses is the standard deviation and third number in the brackets represents the number of years which the mean and standard deviation of each variable are calculated for. For example, the mean of infant mortality for Algeria over the period of this research which is 55 years (from 1960 to 2014) had 76.552 per 1,000 live births with a standard deviation of 50.828. Even though for most of the variables the data is complete (i.e. the data is available for all 55 years of the study) for some of the variables we have some missing values. That is the reason why the number of observations for some variables is less than 55.

We use four common measures of mortality rates: the infant mortality rate, the mortality rate under age five, the adult female mortality rate, and the adult male mortality rate. The reason for using four measures of mortality is that the effects of oil revenues may differ differently across age groups.

The infant mortality rate is the number of deaths of children under age one per 1,000 live births. The mortality rate for under age five is deaths of children under age five per 1,000 live births. The World Bank defines the female (male) adult mortality rates as the probability that those females (males) who have reached age 15 die before reaching age 60. The rates are per 1,000 females (males).

Figure 4 displays the mortality rates used in this paper. Summary statistics are provided in Table 1 Figure 4 is very helpful in understanding the impacts of conflicts that affected mortality rates in the Middle East and North Africa. The most devastating war of the region was an eight-year war between Iran and Iraq from 1980 until 1988. The number of the Iranians killed in the war was very high. According to the data from the World Bank, over 500 thousand people died from both sides combined, most of whom were young males. The numbers do not show a considerable increase in mortality rate of females or children for any of the countries during the war. Another war was the Iraq War from March 2003 until December 2011. As can be seen from the graph, this war also contributed to an increase in mortality rate of adult males. Yet, a third conflict in the Middle East and North Africa began in 2011 which is famous as Arab Spring. In 2011 demonstrations began in Arab countries followed by changes in the political systems of some countries. In countries such as Syria the Arab Spring followed by ongoing conflicts that significantly increased mortality rates.

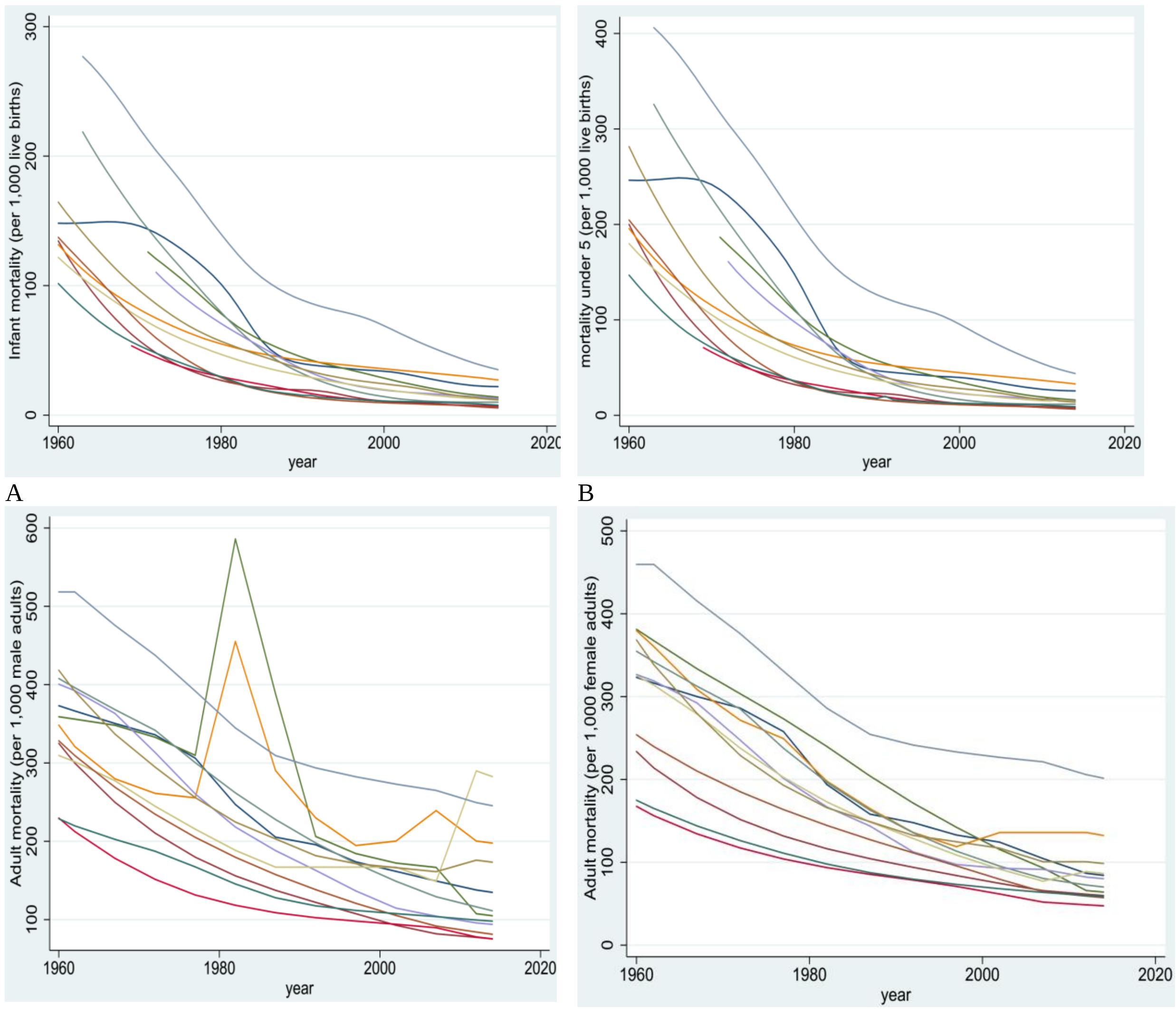
Note that as the table shows mortality rates were usually lowest in countries with small populations, and high GDP and oil revenues per head. Another interesting point is that mortality rates of the treated countries and the control countries are not too different. However, the average of GDP per capita in the treated nations is much higher than that of the control units.

Table 1. Summary statistics

	Infant mortality[a]	Mortality under age 5[b]	Adult mortality female[c]	Adult mortality male[d]	GDP per capita[e]	Daily oil income per head[f]	Oil production[g]	Population (millions)
Algeria	76.552 (50.828) [55]	114.7 (90.357) [55]	191.815 (80.312) [55]	239.147 (82.567) [55]	2731.918 (564.704) [51]	0.656 (0.525) [39]	848.543 (218.606) [39]	23.950 (8.559) [55]
Bahrain	33.849 (32.889) [55]	45.109 (48.897) [55]	116.496 (47.752) [55]	156.541 (70.607) [55]	4237.641 (613.277) [51]	2.724 (2.197) [40]	74.147 (40.565) [40]	0.540 (0.353) [55]
Iran	50.584 (933.024) [55]	68.686 (50.293) [55]	210.315 (97.752) [55]	287.096 (123.036) [55]	4307.478 (1178.294) [55]	1.149 (0.706) [40]	3418.715 (1284.591) [40]	49.409 (18.471) [55]
Iraq	56.276 (27.857) [55]	76.325 (43.366) [55]	201.844 (80.380) [55]	266.796 (64.062) [55]	2857.168 (1543.254) [51]	1.787 (1.681) [40]	1642.842 (757.365) [40]	17.902 (8.003) [55]
Kuwait	30.516 (25.798) [55]	39.865 (37.229) [55]	98.092 (33.836) [55]	144.827 (41.556) [55]	15353.25 (7460.969) [51]	17.281 (11.740) [37]	1726.967 (649.161) [40]	1.629 (0.889) [52]
Libya	56.372 (42.293) [55]	79 (71.735) [55]	176.291 (75.897) [55]	233.701 (75.734) [55]	4343.924 (2156.769) [49]	6.240 (3.941) [20]	1601.439 (575.625) [38]	3.958 (1.618) [55]
Oman	66.119 (63.769) [55]	94.334 (97.212) [55]	185.221 (93.044) [55]	242.024 (95.162) [55]	5616.712 (2548.245) [55]	6.322 (3.686) [38]	543.918 (256.252) [38]	1.693 (0.923) [55]
Qatar	20.841 (13.347) [55]	25.543 (17.582) [55]	91.439 (33.394) [55]	124.339 (40.571) [55]	19353.93 (11838.27) [51]	23.599 (17.242) [40]	460.317 (153.209) [40]	0.546 (0.566) [55]
Saudi Arabia	41.360 (29.280) [43]	55.141 (43.577) [43]	168.055 (82.075) [55]	213.859 (101.162) [55]	9063.92 (2414.286) [51]	10.675 (8.152) [35]	7045.714 (1836.274) [35]	15.062 (8.433) [55]
Syria	44.949 (31.214) [55]	60.5 (46.846) [55]	168.436 (77.840) [55]	212.238 (51.255) [55]	5776.062 (1530.089) [50]	0.502 (0.323) [37]	306.440 (191.489) [37]	11.928 (5.206) [55]
UAE	36.545 (38.057) [55]	49.738 (56.705) [55]	134.962 (58.079) [55]	172.802 (72.505) [55]	19053.39 (6015.65) [51]	21.450 (14.186) [33]	1522.091 (598.432) [33]	2.453 (2.672) [55]
Yemen	121.278 (72.707) [52]	176.111 (110.899) [52]	295.395 (83.139) [55]	349.081 (88.685) [55]	2178.319 (692.059) [55]	.391 (0.232) [19]	269.452 (122.244) [19]	12.648 (16.643) [55]
All countries	54.080 (46.257) [975]	74.889 (71.470) [975]	172.203 (90.181) [1,020]	222.974 (97.474) [1,020]	6648.051 (6653.095) [999]	7.845 (11.329) [436]	1641.967 (1983.831) [439]	12.414 (16.441) [1,024]
Treated countries	53.273 (48.723) [622]	74.308 (75.729) [622]	169.863 (90.383) [660]	220.204 (99.813) [660]	7869.167 (7612.76) [617]	7.845 (11.329) [436]	1641.967 (1983.831) [439]	11.856 (15.414) [675]
Control Countries	55.501 (41.585) [353]	75.914 (63.362) [353]	176.493 (89.777) [360]	228.052 (92.954) [360]	4675.725 (3991.258) [382]	0	0	13.364 (18.041) [385]

Notes: The first number in each cell is the mean. The numbers in the parentheses represent standard deviations and the ones in the brackets are sample counts.

a. Infant mortality (per 1,000 live births)
b. Mortality under age 5 (per 1,000 live births)
c. Adult mortality-female (per 1,000 female adults)
d. Adult mortality-male (per 1,000 male adults)
e. Real GDP per capita in 2011 US dollars
f. The average of oil income of the country per head per day in nominal US dollars
g. Oil production (1000 barrels per day)



C

D

Figure 4. Mortality rates

A. Infant mortality (per 1,000 live births). B. Mortality under age 5 (per 1,000 live births). C. Adult mortality-male (per 1,000 male adults). D. Adult mortality-female (per 1,000 female adults)

Table 2 reports the mean, standard deviation, and number of observations for the treated nations before 1973 and after 1973. The child mortality rate for both groups of the countries has decreased over time. However, the important point is that child mortality rate, including both infant mortality and mortality under age 5, before the event has been more in the treated countries comparing to the control group, but it has been less after the event. The data in Table 2 does not show an improvement in mortality rates of the adults after the treatment comparing with those of the control countries. GDP per capita of the treated nations is more than that of the control group before and after the event, but the difference between the treated and control group has decreased after the event. Note the numbers in Table 2 show the average of the data for each variable over a period of time. This Table only provides some hints about the impact of the oil shock, but the impacts have been estimated and are reported in the next section.

Table 2. Summary statistics treated versus control group before and after the event

	1960-1973		1974-2014	
	Treated	Control	Treated	Control
Infant mortality rate[a]	116.257	106.819	36.631	43.257
	(52.895)	(39.400)	(30.652)	(31.562)
	[130]	[68]	[492]	[285]
Mortality rate under age 5[b]	173.187	158.770	48.181	56.145
	(84.126)	(64.904)	(46.058)	(44.116)
	[130]	[68]	[492]	[285]
Adult mortality rate, female[c]	269.812	272.543	135.735	146.346
	(84.426)	(70.571)	(62.887)	(72.318)
	[168]	[86]	[492]	[274]
Adult mortality rate, male[d]	312.352	327.391	188.739	196.873
	(81.908)	(98.374)	(84.808)	(76.305)
	[168]	[86]	[492]	[274]
GDP per capita[e]	9606.389	2880.831	7219.159	5286.618
	(11098.73)	(1831.396)	(5975.694)	(4331.566)
	[168]	[97]	[492]	[285]
Daily oil income per head[f]	2.261	0	9.257	0
	(2.909)		(12.202)	
	[88]		[348]	
Oil production[g]	1456.367	0	1688.499	0
	(1515.359)		(2084.1)	
	[88]		[351]	
population (Millions)	5.721	8.293	13.964	15.096
	(7.423)	(10.898)	(16.827)	(19.619)
	[168]	[98]	[489]	[287]

Notes: The first number in each cell is the mean. The numbers in the parentheses represent standard deviations and the ones in the brackets are sample counts.

a. Infant mortality (per 1,000 live births)
b. Mortality under age 5 (per 1,000 live births)
c. Adult mortality-female (per 1,000 female adults)
d. Adult mortality-male (per 1,000 male adults)
e. Real GDP per capita in 2011 US dollars
f. The average of oil income of the country per head per day in nominal US dollars
g. Oil production (1000 barrels per day)

1.4 Empirical Results

1.4.1 Difference-In-Differences

Table 3 represents the results of difference-in-differences model (i.e. equation 1). Results for all countries in the data set are reported in column (1). In column (4) Iran and Iraq are dropped from the dataset for two reasons. The first reason goes back to the possibility of endogeneity of the treatment respect to the Iranian economy and the second reason is the Iran-Iraq war from 1980 to 1988 which increased mortality rates in both countries. In column (7), Syria and Algeria as well as Iran and Iraq are dropped from the dataset. Besides the Iran-Iraq war, another reason for dropping those countries is that they had the least oil revenue per capita in 1974 among all producing nations in the sample. By dropping them, we can see the impact of the oil price shock on the nations that income from oil has a bigger contribution to their economies. Note that even though Iran was one of the largest oil producers in the early 70s, but because it had a population of over 30 million people, its oil revenue per capita was less than most of the other oil-producing nations. In column (10), the dataset is limited to 1960-2010. In other words, years 2011 to 2014 are dropped. That is because of Arab Spring which affected Syria, Libya, and Yemen among the treated nations of the research and Tunisia among the countries of the control group. The two columns after columns (1), (4), (7), and (10) show the number of observations and R Squared relevant to DID estimations. All of the regressions contain country and year fixed effects. The equations are estimated with and without GDP per capita as a control variable.

As can be seen in the impacts of the 1973 oil price shock on all measures of mortality and GDP per capita are negative and statistically significant. The results show bigger impacts when GDP per capita is a control variable. The results in the first row and column (1) show that the impact of the oil shock on infant mortality rate is negative 17.21 which means infant mortality decreased by 17.21 per 1000 live infants every year. In addition, in the same column the impact of the oil price shock on mortality rate of children under age 5, is 25.23 fewer deaths per 1000 live births. Also, the impact of the shock on adult female and adult male mortality rates are 1.86 and 16.07 (per 1000 adults) respectively. Note that the absolute value of the impact on adult male mortality is much larger than that of the adult female mortality. The reason for this difference goes back to the Iran-Iraq war where most of the victims were adult males. The impact of the oil price shock on mortality rates of adult males is much larger when Iran and Iraq are dropped.

Also, as mentioned before, the impact of the oil shock on log of GDP per capita is negative and statistically and economically significant. This result confirms the findings of the resource curse literature.

Table 3. Difference-in-differences results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Dependent variable	All countries	N	R2	All countries except Iran and Iraq	N	R2	No Syria, Algeria, Iraq, Iran	N	R2	Arab Spring & no Iran and Iraq	N	R2	Control variable: GDP PC
Infant mortality[a]	-17.218***	975	0.884	-20.156***	876	0.886	-23.067	766	0.884	-23.697***	706	0.890	
	(2.823)			(2.963)			(3.208)			(3.201)			
Mortality under age 5[b]	-25.232***	975	0.869	-29.920***	876	0.871	-31.199***	766	0.870	-32.119***	706	0.878	
	(4.631)			(4.876)			(5.175)			(5.172)			
Adult mortality male[c]	-1.860***	1,020	0.864	-15.205***	910	0.922	-19.560***	800	0.938	-21.220***	744	0.939	
	(5.719)			(4.373)			(4.236)			(4.244)			
Adult mortality female[d]	-16.075***	1,020	0.926	-10.087***	910	0.927	-4.808	800	0.924	-6.038***	744	0.923	
	(3.890)			(3.979)			(4.328)			(4.403)			
Infant mortality[a]	-25.987***	929	0.898	-29.467***	838	0.901	-36.977***	737	0.905	-36.207***	701	0.911	Y
	(2.767)			(2.893)			(3.105)			(3.055)			
Mortality under age 5[b]	-40.065***	929	0.887	-46.058***	838	0.891	-54.080***	737	0.895	-52.801***	701	0.902	Y
	(4.502)			(4.716)			(4.981)			(4.901)			
Adult mortality male[c]	-13.193***	974	0.882	-30.953***	872	0.947	-39.024***	771	0.952	-38.332***	739	0.952	Y
	(5.502)			(3.747)			(3.923)			(3.966)			
Adult mortality female[d]	-30.302***	974	0.945	-26.050***	872	0.944	-24.717	771	0.941	-23.885***	739	0.940	Y
	(3.487)			(3.620)			(4.053)			(4.105)			
Log GDP pc[e]	-0.349***	999	0.808	-0.324***	897	0.826	-0.425***	796	0.827	-0.429***	760	0.825	
	(0.054)			(0.055)			(0.059)			(0.060)			

Notes: All regressions include country and region-year fixed effects. The numbers in parentheses represent standard errors.

a. Infant mortality (per 1,000 live births)
b. Mortality under age 5 (per 1,000 live births)
c. Adult mortality-male (per 1,000 male adults)
d. Adult mortality-female (per 1,000 female adults)
e. Logarithm of real GDP per capita in 2011 US dollars

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

1.4.2 Robustness Check

One concern is that because of the increase in price of oil in 1979 the parallel trend assumption might not hold. Therefore, the analysis is repeated using observations for 1960-1978. The impacts of the 1973 oil price shock on mortality rates that are reported in Table 4 are, to a high extent, similar to the results in Table 3 Even though the size of the dataset is smaller in Table 4 (only five years) the coefficients are not too different from those of the complete dataset in Table 3.

However, in Table 4 the coefficient of Log of GDP per capita is not statistically significant. Perhaps, the reason is that resource curse (the negative impacts of natural resource revenues on economic growth) does not happen as fast as five years after an increase in oil revenues. Note that the reason that Israel has been dropped in the second series of the estimation in Table 4 is that that Israel has a more advanced economy as compared to the countries in the treated group or the ones of control group. Dropping Israel has a very marginal impact on the size of the coefficients without any impact on their signs.

Because the price of oil started to increase in 1970, 1970 might be the year that should be considered as the event year. Hence, the results reported in Table 5 use the event year of 1970. As can be observed, the results are similar to the ones in Table 3 In most cases, the impacts of the oil shock on child and adult mortality rates is negative and statistically significant. Again, the impact of the oil shock on per capita GDP is negative and statistically significant. However, the impact on income is smaller when the event year is 1970 rather than 1973.

Table 4. Robustness check; difference-in-differences estimations. 1960-1978

Dependent variable	All countries	N	R2	All countries except Israel			All countries except Iran	N	R2	Control variable: GDP PC
Infant mortality[a]	-15.457^{***} (4.245)	291	0.957	-15.457^{***} (3.108)	286	0.955	-15.437^{***} (3.150)	283	0.957	
Mortality under age 5[b]	-23.696^{***} (4.849)	291	0.958	-23.696^{***} (4.883)	286	0.957	-23.637^{***} (4.950)	283	0.958	
Adult mortality male[c]	-0.564 (4.235)	344	0.961	-0.564 (4.178)	342	0.962	-3.840 (4.101)	325	0.966	
Adult mortality female[d]	-6.520^{*} (3.584)	344	0.973	-6.520^{*} (3.550)	342	0.973	-6.541^{*} (3.749)	325	0.972	
Infant mortality[a]	-16.546^{***} (3.024)	290	0.959	-16.548^{***} (3.050)	285	0.957	-16.664^{***} (3.095)	282	0.959	Y
Mortality under age 5[b]	-25.719^{***} (4.687)	290	0.962	-25.724^{***} (4.719)	285	0.960	-25.926^{***} (4.789)	282	0.962	Y
Adult mortality male[c]	-0.361 (4.205)	343	0.962	-0.322 (4.141)	341	0.963	-3.845 (4.033)	324	0.968	Y
Adult mortality female[d]	-6.198^{*} (3.520)	343	0.974	-6.169^{*} (3.479)	341	0.974	-6.490^{*} (3.680)	324	0.973	Y
Log GDP pc[h]	0.062 (0.054)	360	0.957	0.086 (0.056)	341	0.956	0.036 (0.053)	341	0.958	

Notes: All regressions include country and region-year fixed effects. The number in parenthesis represent standard errors.

a. Infant mortality (per 1,000 live births)
b. Mortality under age 5 (per 1,000 live births)
c. Adult mortality-male (per 1,000 male adults)
d. Adult mortality-female (per 1,000 female adults)
e. Logarithm of real GDP per capita in 2011 US dollars

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 5. Robustness Check; difference-in-differences estimations. Event year 1970

Dependent variable	All countries	N	R2	All countries except Israel	N	R2	All countries except Iran and Iraq	N	R2	Arab Spring	N	R2	Control variable: GDP PC
Infant mortality[a]	-19.303*** (3.123)	975	0.884	-19.303*** (3.137)	934	0.883	-22.790*** (3.268)	876	0.887	-23.232*** (2.261)	808	0.892	
Mortality under age 5[b]	-28.798*** (5.120)	975	0.869	-28.798*** (5.147)	934	0.869	-34.445*** (5.375)	876	0.872	-35.083*** (5.372)	808	0.878	
Adult mortality male[c]	-2.050 (6.217)	1,020	0.864	1.243 (6.320)	990	0.861	-15.268*** (4.760)	910	0.922	-17.906*** (4.385)	846	0.934	
Adult mortality female[d]	-16.229*** (4.234)	1,020	0.926	-13.404*** (4.282)	990	0.925	-10.286*** (4.328)	910	0.927	-11.095*** (4.382)	846	0.926	
Infant mortality[a]	-26.373*** (3.042)	929	0.896	-27.674*** (2.973)	888	0.901	-30.116*** (3.169)	838	0.900	-29.309*** (3.121)	802	0.905	Y
Mortality under age 5[b]	-40.707*** (4.945)	929	0.886	-42.804*** (4.831)	888	0.892	-46.866*** (5.161)	838	0.889	-45.578*** (5.089)	802	0.895	Y
Adult mortality male[c]	-11.373 (5.911)	974	0.882	-8.054 (5.959)	944	0.881	-27.960*** (4.060)	872	0.946	-27.267*** (4.089)	840	0.946	Y
Adult mortality female[d]	-27.446*** (3.787)	974	0.943	-24.254*** (3.728)	944	0.945	-22.995*** (3.915)	872	0.943	-22.305*** (3.946)	840	0.943	Y
Log GDP pc[h]	-0.285*** (0.059)	999	0.805	-0.231*** (0.063)	944	0.792	-0.262*** (0.060)	897	0.822	-0.264*** (0.061)	861	0.820	

Notes: All regressions include country and region-year fixed effects. The number in parenthesis represent standard errors.

a. Infant mortality (per 1,000 live births)
b. Mortality under age 5 (per 1,000 live births)
c. Adult mortality-female (per 1,000 female adults)
d. Adult mortality-male (per 1,000 male adults)
e. Logarithm of real GDP per capita in 2011 US dollars

*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

1.4.3 Impact on Hospital Beds

The findings of this paper to this point are highly puzzling. Our results show that the oil shock in 1973 had a negative impact on GDP per capita, but improved mortality rates (i.e. decreased mortality). In this section we try to identify the plausible channel through which the windfall revenue from the oil decreased mortality[6]. Here we have estimated the impacts of the oil shock in 1973 on the number of hospital beds per head. In Appendix A the number of hospital beds per head in each country over the period of the research has been represented (i.e. 1960-2014).

As the table shows, the effect of the oil price shock on the number of hospital beds is positive and economically and statistically significant. Assuming that means that the health sector has been growing after the oil shock, then Dutch Disease hypothesis can provide us with a plausible channel that the oil shock could have improved the mortality rate despite its negative impact on economic growth.

One prediction of Dutch Disease is that if the oil sector employs a low ratio of workers of the whole economy (which in practice is the case in any economy), then the spending effect (i.e. increase in aggregate demand in the services sector because of the oil price shock) dominates the resource movement effect (i.e. movement of labor and capital from agriculture and manufacturing sectors to the oil sector because of the oil price shock) which leads to an increase in output and employment in services sector (such as health sector) [7].

[6] Note that other factors such as improvement in water and sanitations might take place after the windfall revenues take place. That also could affect mortality.
[7] see the introduction for more details

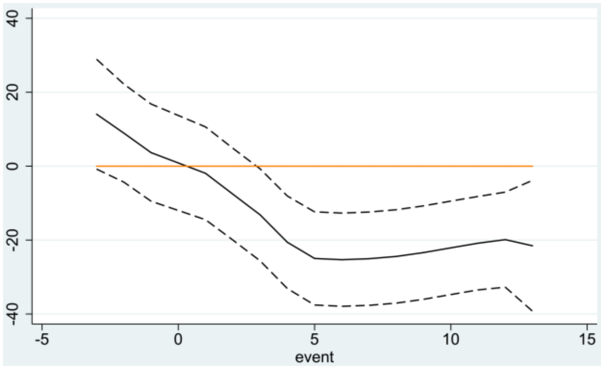
Table 6. difference-in-differences estimations: impacts of the oil price shock on hospital beds

All countries	N	R2	All countries except Iran and Iraq	N	R2	Arab Spring	N	R2	**Control variable:** GDP PC
0.828*** (0.260)	325	0.673	0.713*** (0.288)	287	0.662	0.740** (0.312)	226	0.743	
1.595*** (0.256)	285	0.747	1.556*** (0.284)	255	0.739	1.565*** (0.294)	221	0.699	Y

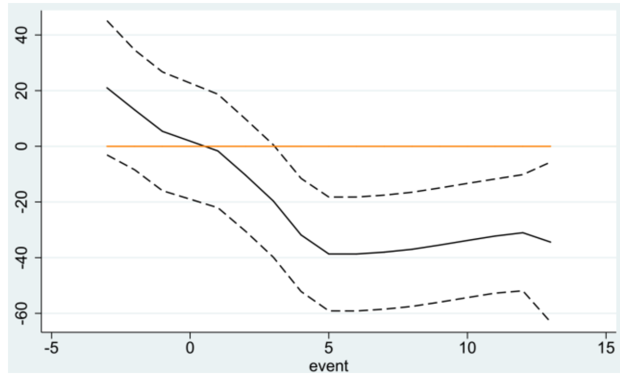
Dependent variable: Number of hospital beds per person. All regressions include country and region-year fixed effects. The number in parenthesis represent standard errors. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

1.4.4 Event Studies

In this section we provide the event study estimations. Instead of the interactions of event and post in equation 1 we have used interactions of event and three-year dummy variables. This specification allows the treatment effect to vary over time. The three-year dummy variable that indicates 1971 to 1973 period (i.e. equals to one if year is 1971, 1972, or 1973 and equals to zero otherwise) has been omitted from the regression. The reason is that identification in this specification comes from comparing the outcome variables to the omitted 3-years period prior the event. Also, the associated estimations are provided in Table 7 As can be seen in the figure and the table, the coefficients are not significant prior to the oil shock in 1973. However, after a few years the significant coefficients appear. As the results show the impacts of the oil shock on mortality rates and economic growth are negative.



A.



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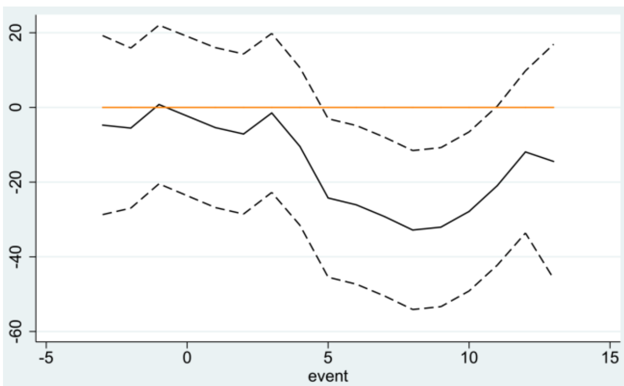

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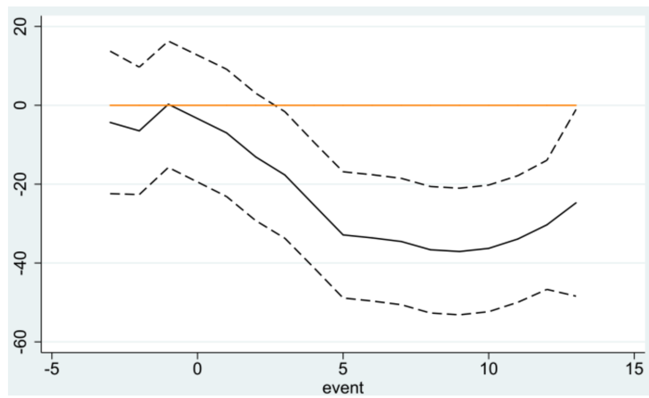

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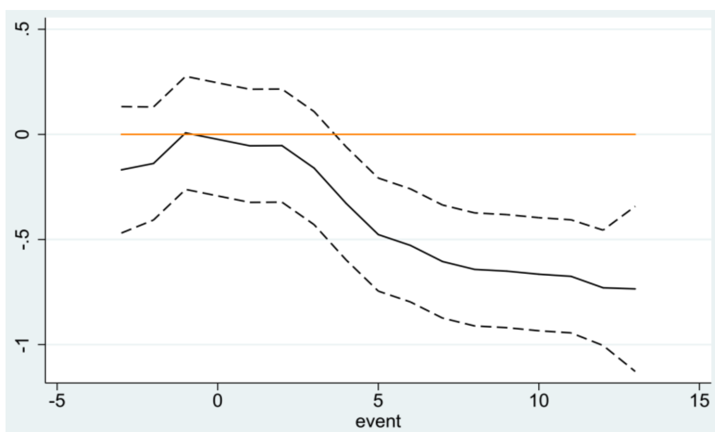


E.

Figure 5. Event studies

A. Infant mortality, B. Mortality under age 5, C. Adult mortality male, D. Adult mortality female, E. GDP per capita

Notes: All regressions include country and region-year fixed effects. the numbers on horizontal axes show the associated event (see Table 7). The numbers on the vertical axes show the size of the coefficient (i.e. interaction of the event and 3-years dummy variables). Event is a dummy variable that equals to one if a country is one of the treated countries and it is equal to zero if the country is a country in the control group.

Table 7. Event study estimations

Event	Event year	Infant mortality	Mortality under age 5	Adult male mortality	Adult female mortality	Log GDP pc
-3	1962 - 1964	14.065* (7.566)	21.02* (12.281)	-4.735 (12.209)	-4.343 (9.205)	-0.168 (0.153)
-2	1965-1967	8.942 (6.752)	13.075 (10.960)	-5.524 (10.917)	-6.478 (8.231)	-0.138 (0.137)
-1	1968-1970	3.665 (6.694)	5.386 (10.856)	0.784 (10.820)	0.265 (8.158)	0.007 (0.137)
0	1971-1973	--	--	--	--	--
1	1974-1976	-1.936 (6.752)	-1.661 (10.382)	-5.399 (10.909)	-7.001 (8.225)	-0.054 (0.137)
2	1977-1979	-7.566 (6.322)	-10.375 (10.262)	-7.111 (10.916)	-13.094 (8.231)	-0.053 (0.137)
3	1980-1982	-13.158** (6.335)	-19.656* (10.283)	-1.475 (10.843)	-17.669** (8.176)	-0.160 (0.137)
4	1983-1985	-20.586*** (6.375)	-31.834*** (10.347)	-10.446 (10.753)	-25.290*** (8.108)	-0.328** (0.137)
5	1986-1988	-24.958*** (6.415)	-38.668*** (10.412)	-24.244** (10.811)	-32.864*** (8.151)	-0.476*** (0.137)
6	1989-1991	-25.301*** (6.421)	-38.678*** (10.422)	-26.082** (10.820)	-33.621*** (8.158)	-0.528*** (0.137)
7	1992-1994	-25.029*** (6.426)	-38.025*** (10.430)	-29.231*** (10.827)	-34.548*** (8.163)	-0.604*** (0.137)
8	1995-1997	-24.414*** (6.433)	-37.004*** (10.442)	-32.825*** (10.838)	-36.639*** (8.172)	-0.642*** (0.137)
9	1998-2000	-23.373*** (6.438)	-35.473 (10.450)	-32.055*** (10.845)	-37.075*** (8.177)	-0.650*** (0.137)
10	2001-2003	-22.098*** (6.439)	-33.827*** (10.451)	-27.860** (10.847)	-36.284*** (8.178)	-0.665*** (0.137)
11	2004-2006	-20.837*** (6.437)	-32.232*** (10.449)	-20.946* (10.844)	-33.908*** (8.176)	-0.675*** (0.137)
12	2007-2009	-19.879*** (6.549)	-31.029*** (10.630)	-11.914 (10.061)	-30.315*** (8.340)	-0.729*** (0.137)
13	2010-2012	-21.545** (9.018)	-34.409** (10.638)	-14.474 (10.996)	-24.730** (12.061)	-0.735*** (0.200)

All regressions include country and region-year fixed effects. The number in parenthesis represent standard errors. The interaction of event and the dummy variable that indicate years 1971 to 1973 is omitted. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

1.4.5 Obtaining Stationary Residuals

Table 8 presents unit root tests results. The reason behind providing this table is that the sample in this paper includes fifty-five time periods and if the residuals of the regressions are not stationary then the findings might not be consistent. So, we do Fisher-type unit-root test on the residuals of the difference-in-differences regressions from the estimates of equation 1. Fisher-type unit-root test is based on Augmented Dickey-Fuller test methodology. References?

The null hypothesis here is that "All panels contain unit roots" and the alternative hypothesis is "At least one panel is stationary". As can be seen in Table 8, for all of the estimations the null hypothesis is rejected at 1% significance level. In other words, we do not see any evidence that the residuals contain unit roots. Therefore, the findings of the difference-in-differences regressions should be consistent

Table 8. Fisher-type unit-root test based on Augmented Dickey-Fuller test

Dependent variable	All countries	Arab Spring & No Iran, No Iraq
Infant mortality	232.884***	160.399***
Mortality under age 5	245.853***	191.537***
Adult mortality male	85.014***	115.488***
Adult mortality female	127.839***	129.473***
Log GDP pc	99.490***	83.168***

Notes: The H0 and Ha hypotheses of Augmented Dickey-Fuller tests are as follow:
Ho: All panels contain unit roots
Ha: At least one panel is stationary
***: reject the null hypothesis at 1% significance level
**: reject the null hypothesis at 5% significance level
*: reject the null hypothesis at 10% significance level

1.5 Conclusion

The focus of this research is on the impacts of the oil price shock of December 1973, on mortality rate of the oil producer nations. We have argued in the paper that the oil price shock in 1973 is an exogenous variable if not for the Iranian economy, but for the rest of the world. We use longitudinal data from 1960 to 2014 and we apply difference-in-differences (DID) methodology to investigate our research questions. Our data covers the Middle East and North Africa region.

Key findings of this research can be summarized as follow:

The oil price increase of 1973 reduced mortality rates in the oil producing nations of the Middle East and North Africa. The findings hold for all measures of mortality: infant mortality rate, mortality rate under age 5, and adult male and female mortality rates. In addition, the results show a negative impact of the oil price shock of 1973 on per capita GDP.

These findings are puzzling. Therefore, we have tried to find the plausible channel through which the oil price shock in 1973 has improved the health sector. We estimated the impact of the oil price shock on number of hospital beds and we found a positive and statistically and economically significant impact on the number of hospital beds.

The results can be explained by Dutch Disease hypothesis. According to the predictions of Dutch Disease hypothesis if the oil sector hires a relatively low percentage of the population a boom in oil prices weakens the manufacturing and agriculture sectors and strengthens the services sector. Since services sector includes health sector and we have found negative impacts of the oil price shock on GDP per capita (this could imply that the effect of the shock on manufacturing and agriculture has been negative[8]) Dutch Disease's prediction might apply to the findings of our study.

The findings indicate that the impact of oil price shock in 1973 on mortality rates in the Middle East and North Africa is negative, but more research is needed to investigate the same research question applying to other contexts. Also, we do not know with confidence whether the findings of this research apply to the other oil producing nations.

[8] GDP includes data from all sectors including oil, manufacturing, agriculture, and services. A decline in GDP is not necessarily because of decline in production of agriculture and manufacturing.

CHAPTER 2
SCHOOLING AND FLUID INTELLIGENCE

2.1 Introduction

Fluid intelligence, which refers to the ability of a person to solve novel problems independent of previously acquired knowledge, is a highly crucial factor in learning and has a big impact on educational and professional success. However, the impacts of formal education on fluid intelligence has been neglected in the literature. In this chapter, we apply an exogenous variation in years of schooling to explore the impacts of education on fluid intelligence. From 1971 to the end of 1973, the global price of crude oil increased over 400%. Such an increase in oil price improved the revenue of the Indonesian government from oil production. Indonesia invested most of the new income on central government's construction projects famous as "Presidential Instructions" (INPRES), which aimed to improve regional equity in the country. The largest INPRES program, known as Sekolah Dasar INPRES, also remains the largest school construction project in history. The government built over 60 thousand elementary schools all over the country from 1973 to 1978. Duflo (2001) studies the impacts of the program on years of education. We have received INPRES data from Duflo and combined it with the Indonesian Family Life Survey (IFLS), which contains individual cognitive ability tests. This dataset represents 83% of the population of 13 out of 26 Indonesian provinces. The results show positive and statistically significant impacts of years of schooling on the fluid intelligence of both females and males. Studies on the return to education generally find positive impacts of the years of schooling on wages. Also, the hypothesis that years of schooling improves crystallized intelligence is generally accepted. Nevertheless, the impacts of education on fluid intelligence are not clearly identified in the literature. First, the number of studies that focus on the impacts of education on fluid intelligence is limited. Second, the existing studies find mixed results. In the following paragraphs, I explain what fluid intelligence means and why it is important to understand the impacts of education on fluid intelligence.

Raymond Cattell (1971) identifies fluid intelligence and crystallized intelligence as two factors of general intelligence. Jaeggi et al. (2008) defines fluid intelligence (Gf) as "the ability to reason and to solve new problems independently of previously acquired knowledge". Fluid intelligence (Gf), which is necessary for all sorts of logical problem-solving tasks, includes both inductive and deductive reasoning. Gf is the capability of a person in understanding patterns and relationships and using logic and abstract reasoning to analyze and solve novel problems. Fluid intelligence is a highly crucial factor in learning and has a big impact on educational and professional success (See Neisser et al. 1996; Deary, 2007; Rohde and Thompson, 2007; and te Nijenhuis et al., 2007 among others)

Crystallized intelligence, however, is the ability to apply experience, knowledge, and skills in solving new problems, and it relies on the information in the long-term memory. Crystallized intelligence (Gc) indicates the life-long acquisition of knowledge through education, language, and culture, and the ability of thinking and reasoning using words and numbers. Therefore, Gc interacts with fluid intelligence as well. Belsky, J.(1990) believes that, because crystallized intelligence relies on knowledge and information, it may start decreasing at an age where the rate of forgetting exceeds the ability to acquire the new knowledge.

Fluid intelligence and crystallized intelligence rely on the function of the two separate sections of the brain. Gc is a function of the sections of the brain that are critical for long-term memories such as the hippocampus, but Gf relies on the functions of those parts of the brain that are involved with short memories and attention such as the anterior cingulate cortex and dorsolateral prefrontal cortex (Geary, 2005). Appendix B represents some graphics that show where the hippocampus, anterior cingulate cortex, and dorsolateral prefrontal cortex are located in the brain.

In the literature, the correlation between fluid intelligence and crystallized intelligence is emphasized because people with higher levels of fluid intelligence typically acquire more crystallized intelligence (Baltes, 1993; Cunha and Heckman, 2007; Dahmann, 2017).

Among the various measures designed to assess fluid intelligence, Raven's Progressive Matrices (RPM), introduced by Raven (1936), is the most common and widely used. Each question in RPM is a multiple-choice question. The test taker sees a window that contains a three by three (or two by two in abbreviated versions) set of drawings, and the last one of them is dropped (i.e. supposed to be nine drawings, but since one of them is dropped the test taker can see eight). The test taker then has to pick the correct dropped drawing among another eight (or six in abbreviated versions) offered choices. Finding the correct answer requires abstract reasoning and identifying one or more underlying relevant features.

Whether Gf can be improved or not has been a topic of debate. At least two studies suggest that training can improve fluid intelligence. In a study by Klingberg et al. (2002) conducted over a period of five weeks, children with ADHD were trained 20 minutes per day and four to six days per week via fluid reasoning computer-based training programs. The children showed an improvement in their working memories and received higher marks in the Raven test scores compared to the control group. In addition, Klingberg et al. (2002) finds a positive impact from a training program on the fluid intelligence of adults, which was assessed by Raven test scores.

Multiple studies have investigated the effects of schooling on cognitive skills (see e.g. Cahan and Cohen, 1989; Ceci, 1991; Herrnstein and Murray, 1994; Stelzl et al., 1995; Neal and Johnson, 1996; Winship and Korenman, 1997; Jacob, 2002; Hansen, Heckman, and Mullen, 2004; Cascio and Lewis, 2006; Cliffordson and Gustafsson, 2007; Carlsson et al., 2015; Dahmann, 2017; Checchi and Paola, 2018; Castro and Rolleston, 2018; Bietenbeck et al., 2019; Jagannathan et al., 2019). Nevertheless, even though it is accepted in the literature that years of schooling improves crystallized intelligence, but the findings on fluid intelligence do not show similar results. The findings of the studies about the impacts of education on fluid intelligence are much more mixed than those of crystallized intelligence. While most of the empirical studies, such as Carlsson et al. (2015) and Cliffordson and Gustafsson (2007), find that length of education has a positive and significant impact on crystallized intelligence, they identify no significant impact on fluid intelligence. Even Cliffordson and Gustafsson (2007), who do not find any significant impact of schooling on fluid intelligence, suggest a negative impact of age on fluid intelligence. However, other researchers such as Cahan and Cohen (1989) and Stelzl et al. (1995) maintain that schooling may influence fluid intelligence.

Note that even though the literature about the potential impacts of schooling on fluid intelligence is mixed, both fluid and crystallized intelligence improved year after year during the 20th century, a phenomenon known as the Flynn Effect. Several explanations such as schooling and test familiarity, generally more stimulating environment, nutrition, and a higher control on infectious diseases are proposed as explanations for the Flynn Effect[9]. One explanation provided by Blair et al. (2005) suggests a neurodevelopmental schooling hypothesis for the Flynn Effect. Based on this hypothesis, an increase in access to school and in cognitively demanding math courses explains the Flynn Effect.

Perhaps the research most similar to our study is Dahmann (2017) that studies the impacts of a high school reform at the state level in Germany between 2001 and 2007. The reform shortened the number of total years of schooling from 13 to 12 years but did not make any other change to the education programs. The results show that the decline in years of schooling led to significantly lower Raven test scores, but Dahmann (2017) argues that this effect could be due to the variation in biological age not the reform. Hence her findings on the impacts of length of education on fluid intelligence should be taken with precaution. It is worth noting that she does not find any significant impact of the reform on the crystallized skills of the students. Dahmann's (2017) study is similar to ours because she investigates the impact of a variation in years of schooling on fluid intelligence. However, her research could be also considered as an opposite case of our study because the years of schooling decreased while we consider the impact of an increase in years of schooling.

Jonsson et al. (2017) finds positive impacts of schooling on fluid intelligence in Nordic Countries, but they mention that this impact is not equal in all Nordic Countries. They argue that differences in the quality of offered math courses, as Blair et al. (2005) emphasizes, might be the reason behind the differences.

Several studies have investigated the impacts of schooling on Armed Forces Qualification Test Scores (AFQT) which is available on NLSY dataset. These studies usually find a positive impact of schooling on AFQT scores (Herrnstein and Murray, 1994; Neal and Johnson, 1996; Winship and Korenman, 1997; Hansen, Heckman, and Mullen, 2004; Cascio and Lewis 2006). Hansen, Heckman, and Mullen (2004) find an average of two to four percentage points increase in AFQT scores, which is twice as large as what Herrnstein and Murray (1994) find, but it is almost equal to the findings of Neal and Johnson (1996) and Winship and Korenman (1997). In addition,

[9] Research suggests that, in the 1990s, a decline in IQ scores began in industrial countries such as France, Norway, the Netherlands, Denmark, Australia, Sweden, Finland, Britain, and German-speaking countries (Cotton et al., 2005; Flynn, 2012; Dutton & Lynn, 2013, 2015; Pietschnig and Gittler, 2015)

most of the studies, such as the one by Hansen, Heckman, and Mullen (2004), find a linear impact of schooling across schooling levels. Also, they argue that the impacts on test score are bigger for participants with lower levels of latent ability[10].

Ceci (1991) finds a positive impact of schooling on general intelligence. However, he argues that, while quantity of schooling positively affects cognition in western nations, this impact is systematically irrelevant to the quality of education. Furthermore, Gustafsson (2016) finds positive and lasting impacts of schooling on adult numeracy performance and literacy in 20 industrial nations.

Based on what has been explained above, the existing literature finds some impacts of education on crystallized intelligence, but it does not present any clear image of the effects of education on fluid intelligence. However, investigating the impacts of education on fluid intelligence is extremely important. First, fluid intelligence plays a significant role in every problem-solving task that a human being executes. Understanding how the current education systems impact fluid intelligence and finding ways to improve education systems such that they could better serve fluid intelligence is highly important. Moreover, because the quality of schools differs between developing countries and developed nations, it is crucial to understand how the education systems of the developing countries affect fluid intelligence. In addition, finding the impacts of education on fluid intelligence helps with an old debate of labor economics: signaling versus human capital views. Positive impacts of education on fluid intelligence is in favor of human capital view rather than signaling.

One important debate in labor economics is the contrast between the Michael Spence's Job Market signaling view and Human Capital view by Gary Becker and others. According to the Signaling view by Spence (1973), a school degree aids prospective employees in revealing their abilities to a potential employer by sending her a signal. In other words, the credential sends a signal to the employer about the unobserved ability of the employee, and that signal enables the employer to distinguish high and low ability workers from each other. Based on Signaling view, education serves an important role in determining the amount of the starting wages of the employees. However, after employees start working, the role of education in determining wages

[10] AFQT measures the skill and knowledge of participants in the areas of arithmetic reasoning, word knowledge, paragraph comprehension, and numerical operations. Hence, it mostly measures crystallized intelligence.

diminishes since their abilities get revealed. Hence, after the employee starts working, the role of ability in determining the amount of income increases over time. According to this theory, people with higher levels of productivity choose higher levels of education to signal their ability to the employers.

According to the Human Capital theory, investment in education increases productivity and therefore income. Credentials do not serve employees only because of their informational value in sending signals to the employers (Becker, 1964; Ben-Porath, 1967). Becker (1992) argues in favor of the Human Capital theory as follows:

> *Tangible forms of capital are not the only type of capital. Schooling, a computer training course, expenditures on medical care, and lectures on the virtues of punctuality and honesty are also capital. That is because they raise earnings, improve health, or add to a person's good habits over much of his lifetime. Therefore, economists regard expenditures on education, training, medical care, and so on as investments in human capital. They are called human capital because people cannot be separated from their knowledge, skills, health, or values in the way they can be separated from their financial and physical assets. Education, training, and health are the most important investments in human capital (p. 1.).*

Arcidiacono et al. (2010) apply the Armed Forces Qualification Test (AFQT) as a measure of ability and provide some insights about education and revealing ability. They find that the ability of college graduates is observed almost perfectly in the job market, but the ability of high school graduates is revealed gradually to the job market over time.

Because of the endogeneity of education and the heterogeneity in individuals' productivity levels, clearly distinguishing signaling effects from human capital in empirical studies is difficult. Therefore, researchers are interested in studying the exogenous variations in education to find support for each of the mentioned views.

We apply an exogenous variation in years of education to study the impacts of education on fluid intelligence. Our results show positive impacts of education on fluid intelligence, which could be interpreted as a finding that is in favor of the human capital view rather than signaling.

The rest of this paper is designed as follows. Section 2 explains the data and identification strategy. Section 3 outlines the empirical design of the paper. Section 4 provides the results and section 5 presents the conclusion of the study.

2.2 Data and Identification Strategy

The data in this research comes from two sources: the Indonesia Family Life Survey (IFLS) and data from Sekolah Dasar INPRES program in Indonesia. The IFLS data is available online. The author has received the Sekolah Dasar INPRES program's data from Esther Duflo[11], an economist from Massachusetts Institute of Technology (MIT). We use IFLS5 which is constructed in 2014 and combine it with Sekolah Dasar INPRES data. Appendix C shows the coverage of IFLS dataset and intensity of Sekolah Dasar INPRES program on map of Indonesia.

2.2.1 Sekolah Dasar INPRES Program

Due to the boom in the global price of oil, oil revenues increased in 1973. The government of Indonesia accessed a higher income to finance the central government's development plans, which is known as "Presidential Instructions" (INPRES). Because of the increase in oil income, the Indonesian government's real expenditure on regional development increased by over 100%. One of the first and by far biggest programs that took place was Sekolah Dasar INPRES, which remains one of the largest school construction projects in human history. From 1973 to 1978, 61,807 elementary schools were constructed all over the country. The number of schools constructed in each region was decided based on the number of primary school aged children in the region who were not enrolled in school in 1972. The stock of the schools doubled between 1971 and 1978. Figure 6 shows the ratio of the total INPRES schools constructed each year (i.e. the number of INPRES schools constructed each year divided by the number of all INPRES schools constructed from 1973 to 1978). In 1973 and 1974, less than 10 percent of the schools were built each year. In 1975 and 1976, over 16 percent of the schools were constructed each year. Finally, in 1977 and 1978, over 23 percent of the schools were built annually.

[11] https://economics.mit.edu/faculty/eduflo

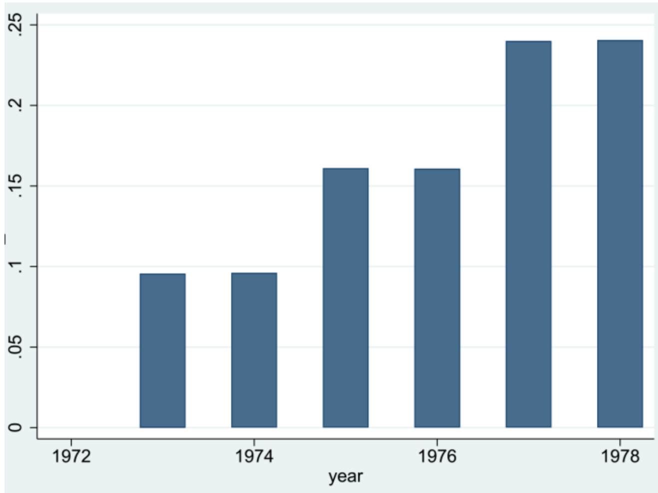


Figure 6. Ratio of the INPRES schools constructed each year
Each bar shows the number of INPRES schools constructed in a particular year divided by the number of all INPRES schools constructed from 1973 to 1978

At the same time, the government initiated a parallel program to increase the number of teachers. New teachers were hired such that the stock of the teachers increased by 43%. Each INPRES school was designed for three teachers and 120 students (Duflo, 2001). Daroesman (1971) argues that the minimum qualification requirements for hiring teachers did not significantly worsen over this period. Hence, the quality of education has not changed significantly.

2.2.2 Indonesia Family Life Survey (IFLS)

The Indonesia Family Life Survey (IFLS) is a continuing longitudinal health and socioeconomic survey that has published data in five waves so far. The data has been conducted by RAND[12] in collaboration with the Demographic Institute at the University of Indonesia, UCLA, Population Research center at University of Gadjah Mad, the center for Population and Policy Studies (CPPS) of the University of Gadjah Mada, and Survey METRE. In the first wave in 1993, the sample of the households in the dataset represented 83% of the population of 13 out of 26 Indonesian provinces. The second, third, fourth, and fifth waves (i.e., IFLS2, IFLS3, IFLS4, IFLS5) were collected in years 1997, 2000, 2007, and 2014, respectively. IFLS5, which is the

[12] Research ANd Development (RAND) is an American nonprofit global policy think tank.

dataset that we use in this research, contains the data of 16,204 households and 50,148 interviewed individuals.

IFLS5 was chosen for this study because in wave five for the first time the respondents of all ages were asked to take an abridged version of the Raven's test, which is a test designed to measure fluid intelligence (Gf). Although participants aged 7-24 were asked to take the same test in IFLS3 and IFLS4, data from IFLS5 was used because we need the respondents who, at the time of taking the Raven's test in 2014, were old enough to be exposed to Sekolah Dasar INPRES program, which took place between 1973 and 1979. The Raven's test used in IFLS5 is available in Appendix D.

2.2.3 Identification Strategy

Exposure to the Sekolah Dasar INPRES program depends on age of the person and region of birth. Since Indonesian children attend elementary school between ages 7 and 12, children aged between 2 and 6 years in 1974 could benefit from the program. However, the ones who were born in 1962 and earlier were too old to go to elementary school. Hence, they did not benefit from the program. The impact of the program for those aged 12 and older in 1974 should be close to zero. For the younger children, exposure is a function of their date of birth. We expect bigger effects from the program on younger children aged 2 to 12 in 1974. The younger the children are the bigger the impact should be.

Region of birth is another factor that determines exposure to the program. Since the goal of the INPRES program was to increase regional equality in Indonesia, the highest numbers of INPRES schools were built in the regions where they were needed the most. As mentioned before, the decision for the numbers of schools built in each region was based on the number of elementary school aged children who were not enrolled in school.

Note that region of education could be endogenous with respect to the program. Duflo (2001) elaborates this point as follows:

> *Because the program intensity was related to enrollment rates in 1972, which differed widely across regions, region of birth is a second dimension of variation in the intensity of the program. Region of birth is highly correlated with the region of education: 91.5 percent of the children in the IFLS sample were still living in the district where they were born at age*

> *12. However, unlike region of education, it is not endogenous with respect to the program given that all individuals in the sample were born before the program was started (p. 798.).*

In this paper, region of birth fixed effect is used in all of the regressions. "Region," here, refers to Indonesian Kabupatens. A Kabupaten in Indonesia is a subregion of a province. If provinces can be considered to be similar to the states in the United States, the Kabupaten could be considered similar to counties.

In our difference-in-differences (DID) estimations, we apply the interactions of INPRES *program intensity* in the region of birth and the *young* to study the impact of the program on education and fluid intelligence. "Program intensity in the region of birth" is the number of constructed INPRES schools in the Indonesian Kabupatens, where an individual was born per 1,000 children. "Young" in our regressions is a binary variable that equals one if someone was 2 to 6 years old in 1974, and it equals to zero for the ones aged 7 to 12.

2.3 Empirical Design

In this paper, the difference-in-differences (DID) approach is applied to estimate the impacts of the INPRES school construction program on years of schooling and fluid intelligence. Two-stage least-squares (2SLS) approach is applied to investigate the impacts of education on fluid intelligence. The basic DID specification is as follow:

$$Y_{ijk} = c_1 + \gamma_1(intens_j \times Young_i) + \delta_1\left(\boldsymbol{C}_j \times Young_i\right) + \alpha_j + \beta_k + \varepsilon_{ijt} \tag{2}$$

where Y_{ijk} is the outcome variable for individual *i*, born in year *k* in region *j*. $Young_i$ is a variable that indicates that individual *i* has been in the young cohort that benefits from the program (i.e. individual *i* ages 2 to 6 in 1974). $Young_i$ is a dummy variable that takes value one if the age of individual *i* has been 2 to 6 in 1974, and it takes value zero if the person's age has been 12 to 17 in 1974. The individuals aged 6 to 12 in 1974 are dropped since they partially benefited from the program. $intens_j$ measures the intensity of the program in region *j*. It is the number of Sekolah Dasar INPRES schools built in the Kabupaten of birth per 1000 children in the region. $\boldsymbol{C}_j$ indicates a vector of control variables. $\boldsymbol{C}_j \times Young_i$ controls for the time-varying region-specific factors that might affect the outcomes. α_j is region of birth fixed effect and β_k is the cohort of birth fixed effect. ε_{ijt} is the error term.

The basic specification in 2SLS approach is:

$$Gf_{ijk} = d + \theta Edu_{ijk} + \alpha_j + \beta_k + \mu_{ijt} \quad (3)$$

where Gf_{ijk} is the fluid intelligence of individual i born in year k in region j. Edu_{ijk} is the years of education of individual i born in year k in region j. ε_{ijt} is the error term, and the rest of the variables have been introduced before.

We apply the interaction between the region of birth and the age of the person as instrument in 2SLS estimations since this instrument is plausibly exogenous after controlling cohort of birth and region of birth effects. Card & Krueger (1992), Card & Lemieux (1998), and Duflo (2001) apply a similar approach.

2.4 Empirical Results

In this section of the paper, the details of the empirical method as well as the empirical results are presented.

2.4.1 Effect on Education

In this section the results of our estimations regarding the impacts of the elementary school construction program on education outcomes are provided.

2.4.1.1 Basic Results

We apply a difference-in-differences (DID) specification to study the impacts of the treatment (i.e. Sekolah Dasar INPRES in Indonesia) on years of education:

Table 9 represents the estimations of equations 2 where the outcome variables is years of education. Three columns are provided in the table. The columns differ based on the control variables used in the regressions. The results are provided in two panels. In Panel A, which is our experiment of interest, $Young_i$ is as described before. It indicates the young cohort who was exposed to the program versus an older cohort who wasn’t exposed to the program. It is equal to one for children aged 2 to 6 in 1974, and is equal to zero for those aged 12 to 17 in 1974. The impact of the school construction program is associated with an increase of 0.29 to 0.35 years of schooling. Panel B represents our control experiment. In panel B, instead of "young" in panel A, we use a dummy variable that sets to one if someone is aged 12 to 17 in 1974, and takes value zero for the ones aged 18 to 24 in 1974. Note that we do not expect to see any significant impact of the program in panel B since people aged 12 to 24 in 1974 were not exposed to the program. As expected, the results of panel B show significantly smaller coefficients with no significant impact from the school construction program on years of schooling.

Table 9. The Impacts of the School Construction Program on Years of Education: Basic Results

	Years of Education		
$intens_j \times Young_i$	(1)	(2)	(3)
Panel A: experiment of interest			
Aged 2 to 6 in 1974	0.352***	0.323**	0.291***
Control: Aged 12 to 17 in 1974	(0.108)	(0.145)	(0.110)
Number of observations	4,188	3,962	3,737
R squared	0.242	0.241	0.318
Panel B: control experiment			
Aged 12 to 17 in 1974	-0.038	-0.108	0.011
Control: Aged 18 to 24 in 1974	(0.096)	(0.109)	(0.097)
Number of observations	3,364	3,205	2,986
R squared	0.175	0.175	0.234
Control variables:			
Year of birth × enrollment rate in 1971	Y	Y	Y
Year of birth × water and sanitation program		Y	Y
Other control variables[1]			Y

Dependent variables: Years of Education
Region of birth and year of birth fixed effects are included in all regressions.
Other control variables include city, village, family size, and electricity. City is a binary variable that indicates whether a person lives in a city. Village is a binary variable that indicates whether a person lives in a village. Family size shows the actual number of household members that live in family. Electricity is a binary variable that determines whether electricity is available in the region of birth.
Young in panel A is a binary variable that takes value one if someone aged 2 to 6 in 1974, and takes value zero for the ones aged 12 to 17 in 1974.
The difference between Panel A and Panel B is that, in panel B, we have used a different binary variable instead of young in Panel A. In Panel B, this variable takes value one if someone aged 12 to 17 in 1974 and takes value zero for the ones aged 18 to 24 in 1974.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

2.4.1.2 Reduced-Form Evidence

The identification strategy of the paper could be generalized by estimating the following regression:

$$Edu_{ijk} = c_1 + \gamma_{1l} \sum_{l=2}^{23} (intens_j \times d_{il}) + \delta_{1l} \sum_{l=2}^{23} (C_j \times d_{il}) + \alpha_{1j} + \beta_{1k} + \varepsilon_{ijt} \qquad (4)$$

where d_{il} is year of birth dummy variable. It takes value one if individual i ages l in 1974. Hence, each coefficient of the interaction of program intensity in the region of birth and d_{il} shows the impact of the program on cohort l. Individuals aged 2 to 24 in 1974 are considered in the range of the estimations, but the ones aged 24 are omitted hence they form the control group. This equation enables us to generalize equation 2 and estimate it cohort by cohort. Because the children aged over 12 in 1974 were not exposed to the program, this regression should not show significant impacts of the treatment on education levels of the cohorts older than 12 years old.

The estimated γ_{1l}s which show the impact of the program on cohort l, are plotted in Figure 7. Also, the same results are presented in Table 10. In Figure 7, the solid line shows γ_{1l}s, and the dashed lines are the 95 percent confidence intervals. γ_{1l} is the coefficient of the interaction of the program intensity (i.e. number of INPRES schools constructed in the region of birth per 1000 children in the region of birth) and cohorts of birth. As expected, since children older than 12 were not exposed to the program, the coefficients for the ones older than 12 randomly vary around zero and are not statistically significant. However, for the cohorts 2 to 12 years-old in 1974, the impact of the program is an increasing function of cohort of birth. The younger children between 2 and 12 are the bigger the impact of the program is on their years of education. These results are expected, and they show that the identification strategy of the paper is correct.

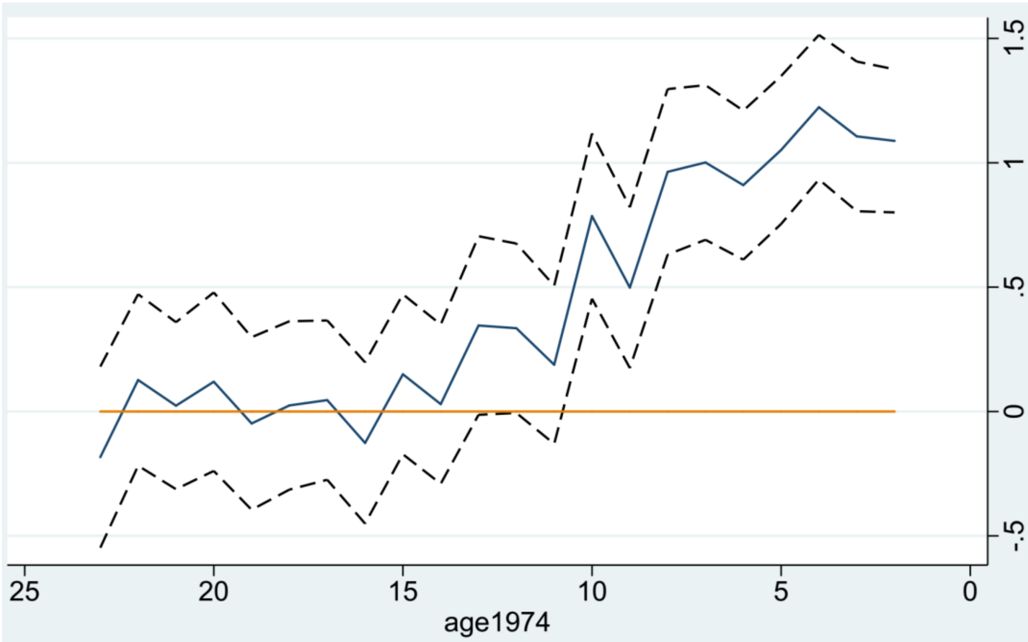


Figure 7. Impacts of the School Construction Program on Years of Education: Reduced-Form Evidence

Dependent variable: Years of Education
The solid line between the two dashed lines show the coefficient of the interaction of cohort of birth and program intensity in the region of birth.
The dashed lines represent a 95 percent confidence interval.
Age in 1974 is on the horizontal axis.
Years of Education are on the vertical axis.

Table 10. The Impacts of the School Construction Program on Years of Education: Reduced-Form Evidence

Age in 1974	$intens_j \times d_{il}$	schooling
23	$intens_j \times d_{i23}$	-0.183 (0.185)
22	$intens_j \times d_{i22}$	0.126 (0.175)
21	$intens_j \times d_{i21}$	0.023 (0.171)
20	$intens_j \times d_{i20}$	0.119 (0.183)
19	$intens_j \times d_{i19}$	-0.048 (0.176)
18	$intens_j \times d_{i18}$	0.024 (0.172)
17	$intens_j \times d_{i17}$	0.045 (0.163)
16	$intens_j \times d_{i16}$	-0.126 (0.165)
15	$intens_j \times d_{i15}$	0.149 (0.164)
14	$intens_j \times d_{i14}$	0.029 (0.163)
13	$intens_j \times d_{i13}$	0.345* 0.183)
12	$intens_j \times d_{i12}$	0.334* (0.173)
11	$intens_j \times d_{i11}$	0.187 (0.162)
10	$intens_j \times d_{i10}$	0.785*** (0.169)
9	$intens_j \times d_{i9}$	0.498*** (0.164)
8	$intens_j \times d_{i8}$	0.963*** (0.169)
7	$intens_j \times d_{i7}$	1.00*** (0.158)
6	$intens_j \times d_{i6}$	0 .910*** (0.152)
5	$intens_j \times d_{i5}$	1.05*** (0.151)
4	$intens_j \times d_{i4}$	1.223*** (0.148)
3	$intens_j \times d_{i3}$	1.106*** (0.153)
2	$intens_j \times d_{i2}$	1.088*** (0.146)
	Number of observations	7,581
	R squared	0.211

Dependent variable: Years of Education

All regressions are clustered by member of family members in each household.

Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

2.4.1.3 Restricted Estimation

In the previous section, we tested whether the impact of the program on years of education of the children older than 12 in 1974 is zero. In this section, however, children older than 12 are omitted from the regression and form the control group. This approach provides us with more precise estimations of the program on the cohorts exposed to it. Estimates of equation 5 provide us with such results.

$$Edu_{ijk} = c_1 + \gamma_{1l} \sum_{l=2}^{12} (intens_j \times d_{il}) + \delta_{1l} \sum_{l=2}^{12} (C_j \times d_{il}) + \alpha_{1j} + \beta_{1k} + \varepsilon_{ijt} \qquad (5)$$

The estimates of γ_{1l} are presented in Table 11. The dependent variable in columns (1) to (3) is years of schooling (i.e. from the first year of elementary to the highest levels of education). The dependent variable in columns (4) to (6) is years of elementary schooling (i.e. 6 years of education in elementary school). In each case, the regressions are presented in three different columns based on the control variables used in the estimations. As can be seen in the table, for children aged 2 to 10 years-old, the impact of the program on years of education is positive and statistically significant. For the ones aged 11 and 12, however, the coefficients are smaller, and they are not statistically significant. These results show that the older students did not benefit from the school construction program as much as students of the younger cohorts did.

Table 11. Impacts of the School Construction Program on Years of Education: Restricted Estimations

		Years of Education			Years of Education at Elementary School		
Age in 1974	$intens_j \times d_{il}$	(1)	(2)	(3)	(4)	(5)	(6)
12	$intens_j \times d_{i12}$	0.282^{**}	0.082	0.044	0.005	-0.016	-0.020
		(0.121)	(0.124)	(0.128)	(0.045)	(0.046)	(0.047)
11	$intens_j \times d_{i11}$	0.135	-0.106	-0.121	0.024	-0.002	0.004
		(0.104)	(0.109)	(0.115)	(0.041)	(0.043)	(0.045)
10	$intens_j \times d_{i10}$	0.731^{***}	0.463^{***}	0.443^{***}	0.182^{***}	0.151^{***}	0.156^{***}
		(0.116)	(0.123)	(0.129)	(0.039)	(0.042)	(0.044)
9	$intens_j \times d_{i9}$	0.443^{***}	0.142	0.129	0.037	0.003	0.009
		(0.109)	(0.118)	(0.126)	(0.039)	(0.042)	(0.046)
8	$intens_j \times d_{i8}$	0.908^{***}	0.566^{***}	0.540^{***}	0.191^{***}	0.154^{***}	0.160^{***}
		(0.118)	(0.128)	(0.137)	(0.038)	(0.042)	(0.046)
7	$intens_j \times d_{i7}$	0.947^{***}	0.568^{***}	0.535^{***}	0.234^{***}	0.196^{***}	0.203^{***}
		(0.102)	(0.116)	(0.126)	(0.032)	(0.037)	(0.042)
6	$intens_j \times d_{i6}$	0.856^{***}	0.459^{***}	0.451^{***}	0.224^{***}	0.181^{***}	0.190^{***}
		(0.092)	(0.107)	(0.122)	(0.031)	(0.037)	(0.043)
5	$intens_j \times d_{i5}$	0.997^{***}	0.568^{***}	0.541^{***}	0.246^{***}	0.199^{***}	0.203^{***}
		(0.089)	(0.109)	(0.125)	(0.028)	(0.036)	(0.042)
4	$intens_j \times d_{i4}$	1.168^{***}	0.699^{***}	0.674^{***}	0.317^{***}	0.266^{***}	0.276^{***}
		(0.086)	(0.108)	(0.127)	(0.026)	(0.034)	(0.042)
3	$intens_j \times d_{i3}$	1.052^{***}	0.554^{***}	0.536^{***}	0.301^{***}	0.246^{***}	0.252^{***}
		(0.093)	(0.117)	(0.136)	(0.030)	(0.039)	(0.046)
2	$intens_j \times d_{i2}$	1.034^{***}	0.479^{***}	0.455^{***}	0.384^{***}	0.324^{***}	0.332^{***}
		(0.080)	(0.113)	(0.135)	(0.026)	(0.038)	(0.047)
	Control variables:						
	Year of birth × enrollment rate in 1971		Y	Y		Y	Y
	Year of birth × water and sanitation program			Y			Y
	Number of observations	7,581	7,538	7,112	8,776	8,726	8,193
	R squared	0.209	0.216	0.214	0.113	0.113	0.112

Dependent variables: Years of Education (columns (1) to (3)) and Years of Education in Elementary School
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

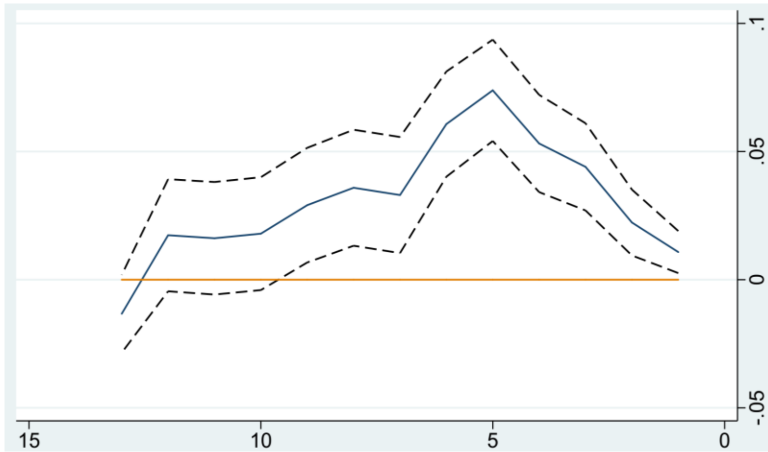
2.4.1.4 Impact on Levels of Education

In this section, we investigate the impact of the school construction program on levels of education. Also, we run separate regressions for females and males to see how differently they get affected by the program. To do so, the following regression is estimated:

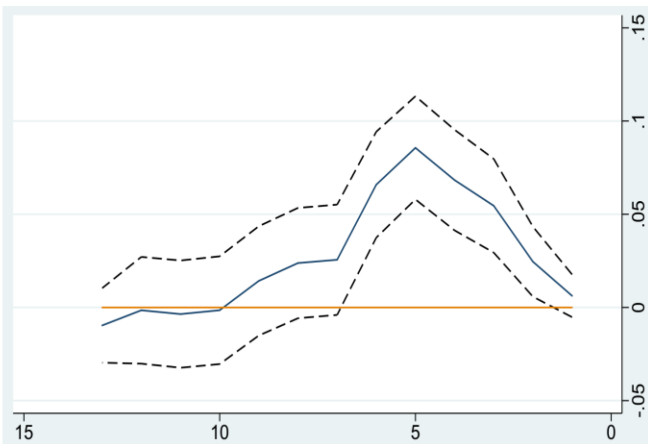
$$Edu_{ijkm} = c + k_m(intens_j \times Young_i) + \alpha_j + \beta_k + \varepsilon_{ijt} \quad (6)$$

where Edu_{ijkm} is a binary variable that sets to one if individual *i* in region *j* born in year *k* has completed *m* years of education or above. This binary variable takes value zero otherwise. We have estimated this regression for m=0 to 13 separately. The results are provided in Figure 8 and Table 12. The solid line between the two dashed lines in Figure 8. A, B, and C. represent the coefficients of the interaction of program intensity and binary variable $Young_i$ (i.e. k_m). The plotted coefficients in Figure 8 are represented in the form of numbers in Table 12. Part A of Figure 8 and the first column of Table 12 show that the program does not have significant impacts on people with 10 or more years of education. Part B of Figure 8 and the second column in Table 12 show the results of estimations of equation 6 for females. As the results show, the program has a significant impact on years of education of female in elementary school but has no significant impact on completing 7 years of education or above. Part C of Figure 8 and the third column in Table 12 represent the results of estimations of equation 6 for males. As can be seen, the program has benefitted the males to the last year of high school (i.e. 12 years of education). However, it does not have much impact on 13 years of education and above.

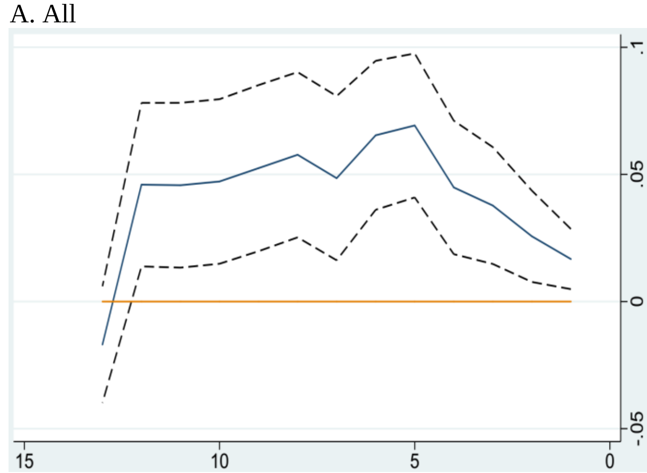
An interesting point in these regressions is that the impact of the program on some years of elementary school education (m=3 to m=6) of the females is larger than that of the males even though the program does not have any significant impact on their education level above elementary school education. One reason for such results could be that, in the poorer areas of the country, the female children would not be sent to school unless the school is nearby. Hence, the school construction program provided a chance for the young women to attend school. This could be the case for a large portion of the male children as well, but in a much smaller rate than that of the female children. Perhaps higher rates of male children were sent to school even if the school was far away from where they lived.



A. All



B. Female



C. Male

Figure 8. The impact of the program on levels of education

A: All children, B: Female, and C: Male.

Dependent variables: Binary variables that take value one if a person completed m years of education or above and they take value zero otherwise. These variables (i.e. Edu_{ijkm}) are on horizontal axes. Region of birth and cohort of birth fixed effects are included in all regressions. Also, the interactions of year of birth and enrolment rate in the region of birth is included in all of the regressions

The solid line between the two dashed lines show the coefficients of the interactions of cohort of birth and program intensity in the region of birth. The dashed lines represent a 95 percent confidence interval. All regressions are clustered by number of family members in each household.

Coefficients (i.e. k_m) are on vertical axes.

Table 12. The Impacts of the School Construction Program on Levels of Education

Edu_{ijkm}	All	Female	Male
m=1	0.010**	0.011	0.016***
	(0.004)	(0.005)	(0.006)
m=2	0.022***	0.024**	0.025***
	(0.006)	(0.009)	(0.009)
m=3	0.044***	0.054***	0.037***
	(0.008)	(0.012)	(0.011)
m=4	0.053***	0.068***	0.044***
	(0.009)	(0.013)	(0.013)
m=5	0.085***	0.073***	0.069***
	(0.014)	(0.010)	(0.014)
m=6	0.065***	0.073***	0.065***
	(0.014)	(0.010)	(0.014)
m=7	0.025*	0.017	0.048***
	(0.015)	(0.011)	(0.016)
m=8	0.035***	0.023	0.057***
	(0.011)	(0.015)	(0.016)
m=9	0.029**	0.014	0.052***
	(0.011)	(0.014)	(0.016)
m=10	0.017	-0.001	0.047***
	(0.011)	(0.014)	(0.016)
m=11	0.016	-0.003	0.045***
	(0.011)	(0.014)	(0.016)
m=12	0.017	-0.005	0.045***
	(0.011)	(0.014)	(0.016)
m=13	-0.013*	-0.009*	-0.016*
	(0.007)	(0.010)	(0.011)
Year of birth × enrollment rate in 1971	Y	Y	Y

Dependent variables: Binary variables that take value one if a person completed m years of education or above and they take value zero otherwise. Region of birth and cohort of birth fixed effects are included in all regressions. Also, the interactions of year of birth and enrolment rate in the region of birth is included in all of the regressions. The upper numbers in each cell show the coefficient of the interaction of program intensity and $Young_i$ (i.e. k_m). Standard errors are in parentheses. All regressions are clustered by number of family members in each household. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Here, we use specifications of equation 2 to further investigate the impact of the program on years of education of the females and males. The results of the estimations are provided in Table 13. In the first three columns of the table, both genders are represented. However, in columns (4) to (6), only females are included in the regressions. In columns (8) to (10), only males are represented. The table shows the coefficient of interactions of school construction intensity in the region of birth and being in the young cohort (i.e. γ_1 in equation 2). The dependent variable in columns (1), (4), and (7) is years of elementary schooling education. Also, the dependent variable in columns (2), (5), and (8) is a binary variable that sets one if a person has completed 6 years of education and above. This variable takes value zero if someone has completed 5 or less years of education. The dependent variable in columns (3), (6), and (9) is a binary variable that sets one if a person has completed 7 years of education and above. This variable takes value zero if someone has completed 6 or less years of education. Note that the impact of the program on the mentioned binary variables is estimated in Table 12, but we have added extra control variables to our estimations in Table 13. Besides the fixed effects, the interactions of year of birth, and enrolment rate in the region of birth, other control variables including the water and sanitation program, city, village, family size, and electricity are added to the regressions. The results confirm our previous findings regarding the impact of the program on education level of the females and males.

The results show that the program had a positive impact on the elementary school education level of the females, but did not have any significant impact their years of education above elementary school. Although we saw that the impact of the program on years 3 to 6 of elementary school education of the females was larger than that of the males in the previous table, the results in Table 13 suggest that the overall impact of the program on elementary school education of the males could be larger than that of the females.

Table 13. The Impacts of the School Construction Program on Education: By Gender

	All			Female			Male		
	(1) Elem. Edu	(2) 6 years & above	(3) 7 years & above	(4) Elem. Edu	(5) 6 years & above	(6) 7 years & above	(7) Elem. Edu	(8) 6 years & above	(9) 7 years & above
$intens_j \times Young_i$	0.198*** (0.039)	0.060** (0.011)	0.023** (0.012)	0.197*** (0.055)	0.064** (0.015)	0.015 (0.110)	0.213*** (0.060)	0.064*** (0.016)	0.038** (0.017)
Number of observations	3,980	3,737	3,737	2,149	1,974	1,974	1,831	1,763	1,763
R squared	0.172	0.222	0.278	0.216	0.279	0.340	0.184	0.238	0.304

Elem. Edu shows the number of years of elementary school that a person has completed. 6 years & above is a binary variable that sets one if a person has completed 6 years of education and above. This variable takes value zero if someone has completed 5 or less years of education. 7 years & above is a binary variable that sets one if a person has completed 7 years of education and above. This variable takes value zero if someone has completed 6 or less years of education.

Region of birth and cohort of birth fixed effects are included in all regressions. The interactions of year of birth and enrolment rate in the region of birth is also included in all of the regressions. The rest of control variables include the water and sanitation program, city, village, family size, and electricity. City is a binary variable that indicates whether a person lives in a city. Village is a binary variable that indicates whether a person lives in a village. Family size shows the actual number of household members that live in family. Electricity is a binary variable that determines if electricity is available in the region of birth.

All regressions are clustered by number of family members in each household.

Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

2.4.2 Effect on Fluid Intelligence

2.4.2.1 Basic Results

Table 14 represents the estimations of equations 2 where the outcome variables is standardized Raven test score. Three columns are provided in the table. The columns differ based on the control variables included in the regressions. The results are presented in two panels. In Panel A, which is our experiment of interest, $Young_i$ indicates the young cohort who was exposed to the program versus an older cohort who was not exposed to the program. It is equal to one for children aged 2 to 6 in 1974, and it equals to zero for those aged 12 to 17 in 1974. The impact of the program on the standardized Raven test score varies from 4.3 to 5.7 percentage points. Panel B represents our control experiment. In panel B, instead of "young" in panel A, we use a dummy variable that sets to one for the ones aged 12 to 17 in 1974, and takes value zero for the others that aged 18 to 24 in 1974. Note that we do not expect to see any significant impact of the program in panel B because people that aged 12 to 24 in 1974 were not exposed to the program. As expected, the results of panel B show significantly smaller coefficients with no significant impact of the school construction program on standardized Raven test score.

Table 14. The Impacts of the School Construction Program on Raven Test Scores: Basic Results

	Standardized Raven Test Scores		
$intens_j \times Young_i$	(1)	(2)	(3)
Panel A: experiment of interest			
Aged 2 to 6 in 1974	0.056***	0.057***	0.043**
Control: Aged 12 to 17 in 1974	(0.020)	(0.021)	(0.019)
Number of observations	4,763	4,473	3,980
R squared	0.117	0.121	0.212
Panel B: control experiment			
Aged 12 to 17 in 1974	-0.005	-0.006	-0.013
Control: Aged 18 to 24 in 1974	(0.017)	(0.017)	(0.017)
Number of observations	3,987	3,777	3,322
R squared	0.112	0.114	0.171
Control variables:			
Year of birth × enrollment rate in 1971	Y	Y	Y
Year of birth × water and sanitation program		Y	Y
Other control variables[1]			

Dependent variables: Raven Test Scores
Region of birth and year of birth fixed effects are included in all regressions.
Other control variables include city, village, family size, and electricity. City is a binary variable that indicates whether a person lives in a city. Village is a binary variable that indicates whether a person lives in a village. Family size shows the actual number of household members that live in family. Electricity is a binary variable that determines whether electricity is available in the region of birth.
Young in panel A is a binary variable that takes value one if someone aged 2 to 6 in 1974, and takes value zero for the ones aged 12 to 17 in 1974.
The difference between Panel A and Panel B is that, in panel B, we have used a different binary variable instead of young in Panel A. In Panel B, this variable takes value one if someone aged 12 to 17 in 1974 and takes value zero for the ones aged 18 to 24 in 1974.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

In Table 14, some basic results of the impact of the program on fluid intelligence measured by Raven test scores are presented and discussed. In this section, we further investigate the impacts of the program on fluid intelligence. Note that our results so far show that the school construction program increased years of education. This provides an exogeneous variation in the years of schooling when controlling for region of birth and cohort of birth effects, which enables us to investigate the causal impacts of education on fluid intelligence.

2.4.2.2 Reduced-Form Evidence

In this section, the estimates of equation 7 provides us with reduced-form evidence where the impact of the program on standardized Raven test scores of cohorts aged 2 to 23 in 1974 is investigated. l=24 is omitted to form our control cohort. The coefficients of the interactions of the program intensity in the region of birth and the cohort dummies determine the impact of the program on Raven test score.

$$Raven_{ijk} = c_2 + \gamma_{2l} \sum_{l=2}^{23} (intens_j \times d_{il}) + \delta_{2l} \sum_{l=2}^{23} (C_j \times d_{il}) + \alpha_{2j} + \beta_{2k} + \epsilon_{ijt} \qquad (7)$$

where d_{il} stands for year of birth dummy variables. It takes a value of one if individual i was age l in 1974. Hence, each coefficient of the interaction of program intensity in the region of birth and d_{il} shows the impact of the program on cohort l. $Raven_{ijk}$ shows the standardized Raven test score of individual i in region j born in year k. α_{2j} and β_{2k} show the region of birth and cohort of birth fixed effects, respectively.

Figure 9 and Figure 10 plot the described coefficients above (i.e. γ_{2l}). Also, the associated results are provided in Table 15. The difference between the mentioned figures comes from the control variables that are applied in the estimations of the regressions. The dashed lines in the figures show the 95 percent confidence interval.

The results show that the program has a positive and significant impact on Raven test score of the children aged 2 to 5 in 1974, but does not confirm any significant impact of the program on the Raven test score of the other cohorts. As expected, the results show that, for the ones aged 12 and older in 1974, the coefficients randomly vary around zero and are not statistically significant. For cohorts younger than 11 years-old in 1974, the size of the coefficients is bigger than that of those 12 years-old and above, but they are not statistically significant.

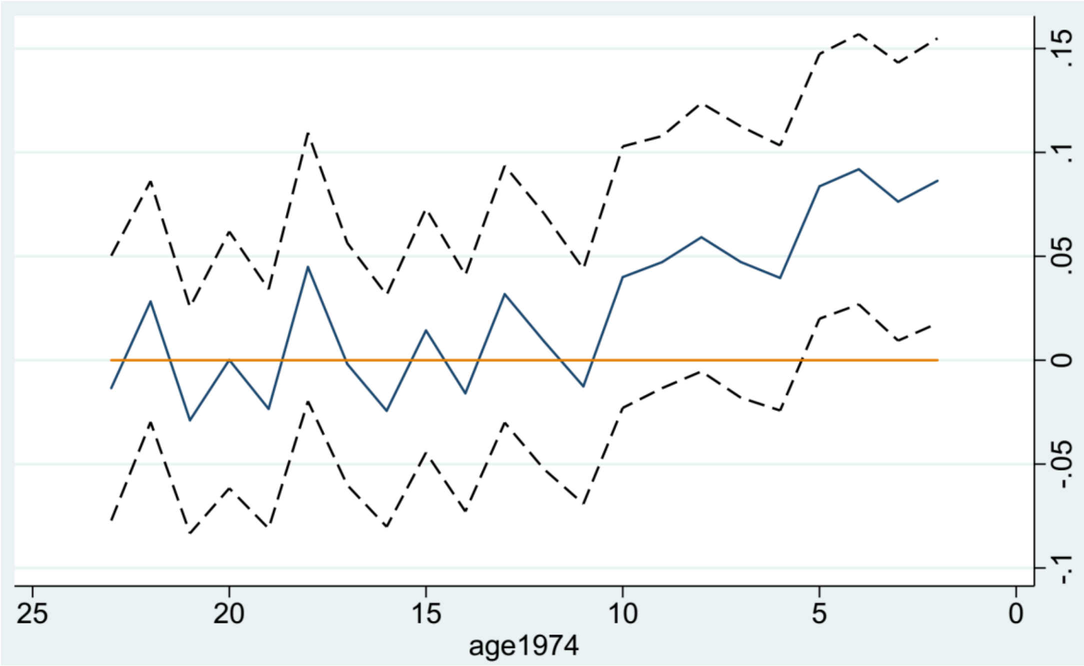


Figure 9. Impacts of the School Construction Program on Raven test score: Reduced-Form Evidence

Dependent variable: standardized Raven test score

The solid line between the two dashed lines show the coefficient of the interaction of cohort of birth and program intensity in the region of birth.

Region of birth and cohort of birth fixed effects are included in all regressions.

The dashed lines represent a 95 percent confidence interval.

Age in 1974 is on horizontal axis.

Standardized Raven test score is on vertical axis.

Year of birth × enrollment rate in 1971 is included.

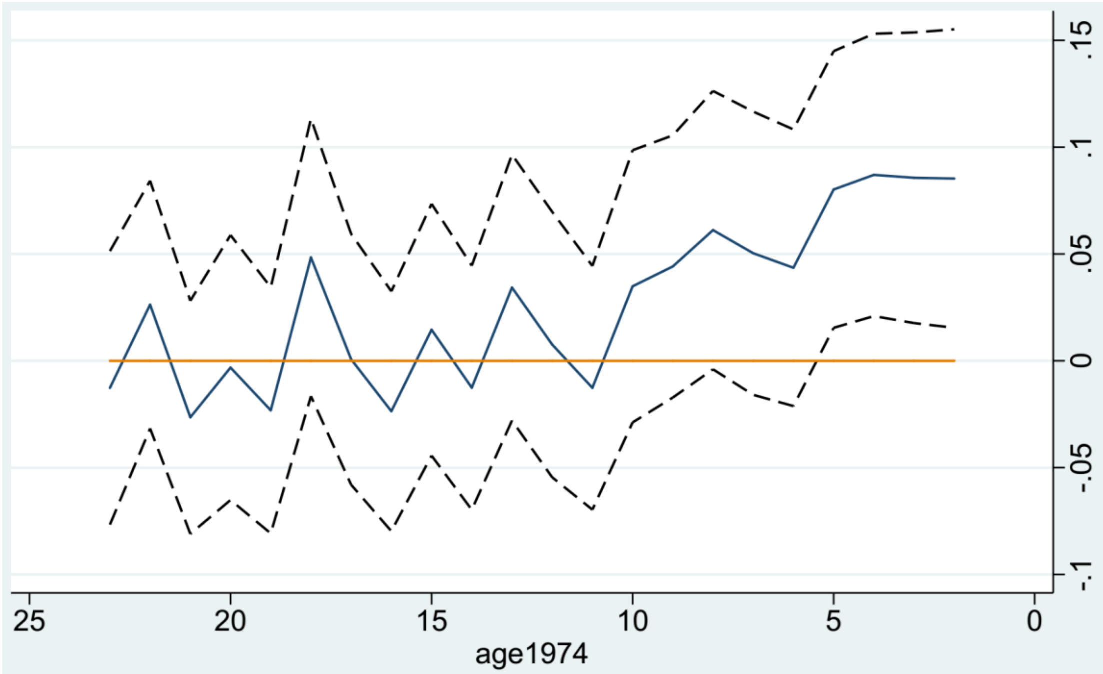


Figure 10. Impacts of the School Construction Program on Raven test score: Reduced-Form Evidence

Dependent variable: standardized Raven test score

The solid line between the two dashed lines show the coefficient of the interaction of cohort of birth and program intensity in the region of birth.

Region of birth and cohort of birth fixed effects are included in all regressions.

The dashed lines represent a 95 percent confidence interval.

Age in 1974 is on horizontal axis.

Standardized Raven test score is on vertical axis.

Year of birth × enrollment rate in 1971 is included.

Year of birth × water and sanitation program is included.

Table 15. Impact of the School Construction Program on Fluid Intelligence: Reduced-Form Evidence

Age in 1974	$intens_j \times d_{il}$	(1)	(2)
23	$intens_j \times d_{i23}$	-0.013 (0.032)	-0.012 (0.032)
22	$intens_j \times d_{i22}$	0.028 (0.029)	0.026 (0.029)
21	$intens_j \times d_{i21}$	-0.028 (0.027)	-0.026 (0.002)
20	$intens_j \times d_{i20}$	0.0001 (0.031)	-0.003 (0.031)
19	$intens_j \times d_{i19}$	-0.023 (0.029)	-0.023 (0.029)
18	$intens_j \times d_{i18}$	0.044 (0.032)	0.048 (0.033)
17	$intens_j \times d_{i17}$	-0.001 (0.029)	0.0007 (0.029)
16	$intens_j \times d_{i16}$	-0.024 (0.028)	-0.023 (0.028)
15	$intens_j \times d_{i15}$	0.014 (0.029)	0.014 (0.030)
14	$intens_j \times d_{i14}$	-0.015 (0.029)	-0.012 (0.029)
13	$intens_j \times d_{i13}$	0.031 (0.031)	0.034 (0.031)
12	$intens_j \times d_{i12}$	0.0090 (0.031)	0.007 (0.031)
11	$intens_j \times d_{i11}$	-0.012 (0.028)	-0.012 (0.029)
10	$intens_j \times d_{i10}$	0.039 (0.032)	0.034 (0.032)
9	$intens_j \times d_{i9}$	0.047 (0.030)	0.044 (0.031)
8	$intens_j \times d_{i8}$	0.059* (0.032)	0.061** (0.033)
7	$intens_j \times d_{i7}$	0.047 (0.033)	0.050 (0.033)
6	$intens_j \times d_{i6}$	0.039 (0.032)	0.043 (0.033)
5	$intens_j \times d_{i5}$	0.083** (0.032)	0.080** (0.033)
4	$intens_j \times d_{i4}$	0.091*** (0.033)	0.087** (0.033)
3	$intens_j \times d_{i3}$	0.076** (0.034)	0.085** (0.034)
2	$intens_j \times d_{i2}$	0.086** (0.034)	0.085** (0.035)
	Control variables:		
	Year of birth × enrollment rate in 1971	Y	Y
	Year of birth × water and sanitation program		Y
	Number of observations	8,722	8,189
	R squared	0.108	0.112

Dependent variable is standardized Raven test score in all cases. Region of birth and cohort of birth fixed effects are included in all regressions. All regressions are clustered by number of family members in each household. Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

2.4.2.3 Restricted Estimation

Estimations of equation 8 give us a more precise understanding of the impacts of the program on Raven test scores. Children aged over 12 in 1974 are dropped from the regressions to form the control group:

$$Raven_{ijk} = c_2 + \gamma_{2l} \sum_{l=2}^{12} (intens_j \times d_{il}) + \delta_{2l} \sum_{l=2}^{12} (C_j \times d_{il}) + \alpha_{2j} + \beta_{2k} + \epsilon_{ijt} \tag{8}$$

where d_{il} stands for year of birth dummy variables. This variable takes value one if individual i ages l in 1974. Each coefficient of the interaction of program intensity in the region of birth and d_{il} shows the impact of the program on cohort l. As mentioned before, cohorts aged 13 to 24 in 1974 are omitted from the estimations to form the control group. $Raven_{ijk}$ shows the standardized Raven test score of individual i in region j born in year k and α_{2j} and β_{2k} show and region and cohort of birth fixed effects, respectively.

The results are presented in Table 16. In column (1) of Table 16, where region of birth and cohort of birth fixed effects are included but not any other control variables, the impact of the program on standardized Raven test score of the cohorts aged 2 to 10 in 1974 is positive and statistically significant. However, the impact of the program on cohorts aged 11 and 12 is much smaller and statistically significant only at 10 percent level. In column (2), besides region of birth and cohort of birth fixed effects, the interactions of year of birth and enrollment rate in 1971 are included as control variables. In column (2), the coefficients are smaller than those of column (1), but they are also statistically significant for the cohorts aged 2 to 10 in 1974. In column (3), besides our usual fixed effects and the interactions of year of birth and enrollment rate in 1971, interactions of year of birth and water and sanitation program are included as control variables. The results in column (3) show significant impacts of the program on the standardized Raven test score of cohorts younger than 9 years old. In column (3), the size of the coefficients is not too different from those of column (2). The size of the coefficients in column (1) is as big as 18.6 percentage points, but varies from 3.7 to 8.9 percentage points in column (2), and from 3.9 to 8 percentage points in column (3).

Table 16. Impact of the School Construction Program on Fluid Intelligence: Restricted Estimations

Age in 1974	$\boldsymbol{intens_j \times d_{il}}$	standardized Raven test score (1)	(2)	(3)
12	$intens_j \times d_{i12}$	0.041*	0.007	0.004
		(0.021)	(0.022)	(0.022)
11	$intens_j \times d_{i11}$	0.030*	-0.013	-0.015
		(0.017)	(0.018)	(0.018)
10	$intens_j \times d_{i10}$	0.087***	0.038**	0.031
		(0.021)	(0.022)	(0.023)
9	$intens_j \times d_{i9}$	0.101***	0.045**	0.040*
		(0.018)	(0.020)	(0.021)
8	$intens_j \times d_{i8}$	0.120***	0.057**	0.057**
		(0.021)	(0.023)	(0.023)
7	$intens_j \times d_{i7}$	0.113***	0.045**	0.046**
		(0.020)	(0.023)	(0.023)
6	$intens_j \times d_{i6}$	0.110***	0.037*	0.039*
		(0.019)	(0.022)	(0.022)
5	$intens_j \times d_{i5}$	0.160***	0.081***	0.075***
		(0.018)	(0.021)	(0.021)
4	$intens_j \times d_{i4}$	0.175***	0.089***	0.082***
		(0.018)	(0.022)	(0.023)
3	$intens_j \times d_{i3}$	0.166***	0.073***	0.080***
		(0.019)	(0.023)	(0.024)
2	$intens_j \times d_{i2}$	0.186***	0.083***	0.079***
		(0.018)	(0.024)	(0.024)
	Control variables:			
	Year of birth × enrollment rate in 1971		Y	Y
	Year of birth × water and sanitation program			Y
	Number of observations	8,772	8,722	8,189
	R2	0.102	0.107	0.111

Dependent variable is standardized Raven test score in all columns. Region of birth and cohort of birth fixed effects are included in all regressions. All regressions are clustered by number of family members in each household. Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

2.4.3 Two-Stage Least-Squares Estimates

Consider the following equation that estimates the impacts of years of education on Raven test scores:

$$Raven_{ijk} = d + \theta Edu_{ijk} + \alpha_j + \beta_k + \mu_{ijt} \tag{9}$$

where all the variables are introduced before. If years of education is not endogenous, then least-square estimates of this equation would reflect the casual effect of education on Raven test scores. However, if there is correlation between education and error term in equation 9, the result of the least-square estimation is biased.

One of the most famous examples of endogeneity in empirical economics is when education is one of the right-hand-side variables in an equation. Endogeneity of education when wage is the dependent variable has been heavily discussed in the return to education literature. In recent decades, many researchers have discussed that education is an endogenous variable in such regressions due to omitted variable bias. A variable that plausibly affects both education and wages is innate ability. In general, a good measurement of innate ability is not available in most of the datasets because it is not an easy variable to measure. When innate ability is omitted from a return to education regression, it will automatically be included in the error term of the regression. Therefore, the innate ability that affects both education and wages and has been included in the error term of the regression, causes a correlation between wages and education. This will cause biased estimates of return to education if least-square estimation is applied. In the case of our research where we are concerned with the impacts of education on fluid intelligence, omitted variables might cause endogeneity and biased estimations. To overcome this issue, we apply the instrumental variables (IV) approach. The interactions between cohorts of birth and program intensity in the region of birth are used as instruments in our 2SLS estimations. We modify equation 9 to incorporate the control variables in the following specification:

$$Raven_{ijk} = d + \theta Edu_{ijk} + \pi_l \sum_{l=2}^{12} (C_j \times d_{il}) + \alpha_j + \beta_k + \mu_{ijt} \tag{10}$$

Also note that equation 5 has been used as the first stage of the two-stage least-square estimations. We have presented the results of least-square estimations in Table 17 and those of the two-stage least-square estimations in Tables 18 and 19.

In Table 17, θs (i.e. the coefficients of years of schooling, Edu_{ijk}) are presented in the table. In the first two columns, both female and male children are represented, while columns (3) and (4) include only female children, and columns (5) and (6) include only male children in the regressions. The findings presented in Table 17 show that an extra year of education is associated with an average of 6.2 to 6.6 percentage points increase in standardized Raven test score.

Table 17. **The Impact of Years of Education on Fluid Intelligence: Least Square Estimations**

	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Schooling	0.066***	0.066***	0.067***	0.068***	0.062***	0.065***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Number of observations	7,653	6,787	3,920	3,554	3,733	3,233
R squared	0.214	0.277	0.267	0.287	0.206	0.285
Control variables:						
Year of birth × enrollment rate in 1971	Y	Y	Y	Y	Y	Y
Other control variables[1]		Y		Y		Y

Dependent variable is standardized Raven test score in all columns.
All regressions include region of birth and cohort of birth fixed effects.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

As previously discussed, the results in Table 17 could be biased due to endogeneity of education. Hence, we have provided the results of 2SLS estimations in Table 18 and Table 19. The estimations in Table 18 include both genders, but separate regressions have been estimated for females and males in Table 19.

The overall results of the 2SLS estimations show that the program has a positive and significant impact on the Raven test scores of both genders. The coefficients in Table 18 vary between 15.3 to 17.7 percentage points. That means that an extra year of education is associated with an average of 15.3 to 17.7 percentage points increase in the standardized Raven test score. At the same time, these findings confirm the positive and significant impact of the school construction program on Raven test scores.

Table 18. Impact of Years of Education on Fluid Intelligence: Two-Stage Least-Square Estimations

		(1)	(2)	(3)
Schooling		0.153^{***}	0.154^{***}	0.177^{***}
		(0.002)	(0.009)	(0.013)
Test of Week instruments	F	43.006	40.789	24.179
Tests of overidentifying restrictions	Sargan (score) chi2	11.482	9.536	15.623
		(p=0.321)	(p=0.491)	(p=0.110)
	Basmann chi2	11.160	9.160	15.147
		(p=0.345)	(p=0.516)	(p=0.126)
Year of birth × enrollment rate in 1971		Y	Y	Y
Water and sanitation program			Y	Y
Other control variables[1]				Y
Number of observations		7,577	7,151	6,718
R squared		0.049	0.051	0.008

Dependent variable is standardized Raven test score in all columns.
All regressions include region of birth and cohort of birth fixed effects.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

In Table 19, the results of the 2SLS estimations are provided for females (columns (1) to (3)) and males (columns (4) to (6)) separately. Again, the results show positive and significant impacts of the school construction program on Raven test scores. The findings show that an extra year of education is associated with an average of 15.8 to 16.6 percentage points increase in the standardized Raven test score of the females. Also, an extra year of education is associated with an average of 14.6 to 18.4 percentage points increase in standardized Raven test score of the males.

Table 19. Impact of Years of Education on Fluid Intelligence by gender: Two-Stage Least-Square Estimations

		female			male		
		(1)	(2)	(3)	(4)	(5)	(6)
Schooling		0.158***	0.158***	0.166***	0.146***	0.147***	0.184***
		(0.011)	(0.011)	(0.016)	(0.015)	(0.016)	(0.019)
Test of Week instruments	F	30.300	28.658	15.586	15.827	15.128	9.724
Tests of overidentifying restrictions	Sargan (score) chi2	9.966 (p=0.443)	7.383 (p=0.688)	10.341 (p=0.411)	3.605 (p=0.963)	3.699 (p=0.959)	10.11 (p=0.430)
	Basmann chi2	9.945 (p=0.489)	6.987 (p=0.726)	9.761 (p=0.461)	3.404 (p=0.970)	3.487 (p=0.967)	9.498 (p=0.485)
Control variables:							
Year of birth × enrollment rate in 1971		Y	Y	Y	Y	Y	Y
Water and sanitation program			Y	Y		Y	Y
Other control variables[1]				Y			Y
Number of observations		3,886	3,667	3,521	3,691	3,484	3,197
R squared		0.095	0.095	0.094	0.055	0.057	0.049

Dependent variable is standardized Raven test score in all columns.
All regressions include region of birth and cohort of birth fixed effects.
All regressions are clustered by number of family members in each household.
Standard errors are in parentheses. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

2.5 Conclusion

Fluid intelligence, defined as the ability of a person to reason, find patterns, and solve novel problems independent of previously acquired knowledge, is highly crucial in learning, accomplishing any logical-solving problem, and has a big impact on educational and professional success (Neisser et al. 1996; Deary, 2007; Rohde and Thompson, 2007; and te Nijenhuis et al., 2007, Jaeggi et al., 2008).

Generally, in the literature it is accepted that years of schooling improves crystallized intelligence, but its impacts on fluid intelligence has not been clearly identified. Studies on the impacts of length of education on fluid intelligence are rare, and the ones that exist have reported mixed results.

Another reason why fluid intelligence is important as a focus of research relates to the new ways of life in a high tech and complicated world. As time passes, high-tech companies shape the world and hire people with capabilities of understanding new technologies. The new generations of laborers have to be capable of solving cognitively demanding novel problems much more than what was expected in the past. As time passes and a larger portion of the world's wealth goes to people with better understanding of technology, the ones who lack the required skills of the new world will be left behind much more than in the past.

In addition, schools are the main institutions that civilized societies have designed for the purpose of education. Education is expensive and time consuming. People in wealthier nations spend one or two decades of their lives on education. However, such an investment is not affordable to billions of people in poorer nations and developing countries. The return to education literature finds positive impacts of length of education on wages. Therefore, the gap between those who can afford to invest in education and those who cannot grows bigger. Moreover, another question relates to the impact of formal education on cognitive abilities. If formal years of schooling affects cognitive abilities, the inequality between rich and poor will be affected. Previously, studies have found positive impacts of years of schooling on crystallized intelligence, and that is not surprising because crystallized intelligence is about acquiring knowledge. How does years of schooling affect fluid intelligence, which is about reasoning and applying logic independent of any acquired knowledge? The answer to this question is essential not only because it tells us about the contribution of formal education to inequality, but also because it is highly essential for the labor market. It is important to know whether more educated employees have stronger capabilities in solving novel problems applying reason and logic.

Furthermore, the answer to this question also helps with the old debate of signaling and human capital of labor economics. According to the signaling view a school degree is important because of its informational value. Credentials reveal the ability of the prospective employees to the employers. However, according to the human capital view, investment in education increases productivity and therefore income of the employees.

One issue in studying the impacts of education on wages or intelligence is the endogeneity of education. An exogeneous variation in years of schooling helps to overcome this issue. This research applies the Indonesian Sekolah Dasar INPRES school construction program, which took place between 1973 and 1978, as an exogenous variation in education to study the impacts of schooling on fluid intelligence.

The results show that the Indonesian Sekolah Dasar INPRES school construction program had a positive and significant impact on years of schooling. In addition, we find positive impacts of years of education on fluid intelligence.

One of the results of this paper is that the program does not equally affect the years of schooling of males and females. It has a significant impact on the years of elementary schooling education of females, but does not have any impact on their levels of education beyond 6 years of schooling. It has a slightly smaller impact on years of elementary schooling of males, but the effect on education of males continues to the last years of high school. The program does not have any impact on years of education beyond high school. Moreover, even for males, the impact on years of high school is significant, but it is not as big as that of the elementary school.

We find significant and positive impact of the program on years of education of the females to the end of their elementary school education, but we did not find any significant impact on their years of education above elementary school. However, our results suggest that the impact of the program on years of education of the males is significant and positive to the end of high school even though it does not have significant impacts on their education beyond high school. Findings of our two-stage least-square specifications suggest that the impact of years of education on fluid intelligence of both females and males is significant and positive and it is not too different across gender.

The findings show that an extra year of education is associated with 15.8 to 16.6 percentage points increase in the standardized Raven test score of females. Also, an extra year of education is associated with 14.6 to 18.4 percentage points increase in the standardized Raven test score of the males.

The findings of this paper are intrinsically important because they tell us about the impacts of education on fluid intelligence. Furthermore, these findings could complete a part of the puzzle of the return to education literature in the labor market that is concerned with wages. Our findings help with understanding why schooling improves wages. Based on the results of this research, one answer is that more educated employees have higher capabilities to find patterns, apply reason, and knowledge in solving novel problems. This finding supports Gary Becker’s human capital rather than Michael Spence's signaling view.

CHAPTER 3
DOES SCHOOLING CAUSALLY IMPACT NON-COGNITIVE SKILLS? EVIDENCE FROM ELIMINATION OF SOCIAL SECURITY STUDENT BENEFITS

3.1 Introduction

In this chapter, we apply the elimination of Social Security student benefits that took place in the United States in 1982 to study the impacts of education on non-cognitive skills measured by Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale. We apply eligibility for aid due to death of father to avoid endogeneity in our analysis. The results confirm that the Social Security student aid program had positive impacts on educational outcomes. Also, our results suggest that non-cognitive skills improve during the college education years, but the causality relationship from college education to non-cognitive skills to a high extent disappear when the previous levels of non-cognitive skills are controlled for. Limited number of studies have investigated the impacts of education on non-cognitive skills, yet they offer mixed results. A few studies suggest that schooling does not significantly affect self-esteem or locus of control, yet other researchers report positive impacts of education on either self-esteem or locus of control. The elimination of Social Security student benefits enables us to investigate the causal impact of schooling on self-esteem and locus of control. Hence the results of this chapter shed light on the impacts of schooling on non-cognitive skills. The two well-known measures of non-cognitive skills, the locus of control scale and the self-esteem scale, have important educational and professional applications. Numerous studies focus on estimating the impacts of non-cognitive skills on important life outcomes, but studies on the impacts of formal schooling on non-cognitive skills remains rare. While researchers have paid attention to the impacts of education on cognitive skills, little attention is given to non-cognitive skills. Focus has been especially centered on crystallized intelligence (Ceci, 1991; Herrnstein and Murray, 1994; Stelzl et al., 1995; Neal and Johnson, 1996; Winship and Korenman, 1997; Hansen et al, 2004; Blair et al, 2005; Cascio and Lewis 2006; Cliffordson and Gustafsson, 2007; Arcidiacono et al., 2010; Carlsson et al., 2015; Gustafsson, 2016; Jonsson et al., 2017).

The main focus of the previous studies relevant to this paper has been on the impacts of schooling on cognitive skills, but little attention has been given to understanding the impacts of schooling on non-cognitive skills. In addition, the existing studies provide mixed results. Some argue that education affects non-cognitive skills, but others claim that those impacts are significant for younger students, but not for the adolescents and adults. Also, it has been discussed that positive impacts of schooling on non-cognitive skills disappear after controlling for previous levels of non-cognitive skills. In short, the findings of the previous studies are highly mixed. In this research, we apply a shift in Social Security students aid policy that took place in 1982 to study the impacts of an exogenous variation in years of schooling on non-cognitive skills. The reason for this approach is that endogeneity of education is a well-known issue in studying the impacts of education on wages and intelligence. Applying an exogeneous variation in years of schooling helps to overcome this issue. Hence, we apply a source of variation in schooling that is exogenous to unobservable variables that might influence non-cognitive abilities. We apply a shift in aid policy that affects the school attendance of some students but not all of them to control for endogeneity of education.

Perhaps the most relevant study to ours is the one conducted by Heckman et al. (2013). In their research, Heckman and his co-authors study the outcomes of the Perry Preschool Project (1962 to 1967) a randomized trial with a control group designed to provide preschool education to 3 to 4 years-old children living in poverty. The project had long-term effects on male income, adult crime rate, and test scores. However, it did not have any significant and lasting impact on IQ. Heckman et al. (2013) argue that the positive effects of the program are due to improvements in the non-cognitive abilities of the children. Also, Dee and West (2011) study the non-cognitive returns to class size and find that the reduction in the 8th grade class sizes in Germany is associated with an improvement in non-cognitive skills. Nevertheless, there has been doubt about the impacts of college education on non-cognitive skills even though the impacts could be strong in younger ages. For example, Bachman et al. (1978) finds that college education has little or no impact on self-esteem. Other researchers such as Kautz et al. (2014), however, argue that non-cognitive skills are malleable in adolescent years and early adulthood and they are influenced by families and years of schooling[13].

Psychologists have been studying personality traits[14] for a long time as compared with economists. When two influential studies by Heckman and co-authors were published, economists began paying attention to the non-cognitive literature. Nevertheless, the term "non-cognitive" has remained as controversial since then. The first of the two studies by Heckman and Rubinstein (2001) suggest that non-cognitive skills contribute to difference in the earnings of the two groups of GED recipients and high school graduates with similar degrees. They argue that the reason behind the difference in the income of the mentioned groups is that the GED recipients have a shortfall of non-cognitive skills compared to the high school graduates. Heckman et al. (2006) applied the National Longitudinal Survey of Youth 1979 to study the importance of non-cognitive skills. They apply the two measurements of non-cognitive skills, including Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale, available in NLSY 1979 dataset, and they suggest that non-cognitive abilities are equally as important as cognitive abilities in determining a variety of social and economic outcomes. Heckman et al. (2006) offer two paths through which non-cognitive abilities, including locus of control and self-esteem, could improve earnings. One path is direct effects on productivity in the labor-market, and the other is through the indirect effects of non-cognitive abilities on schooling and work experience.

There has been a debate in the literature on the importance of self-esteem, one of the two measurements of non-cognitive skills in this paper, in predicting life outcomes. In a research conducted by Boden, et al. (2007, 2008), the impacts of self-esteem on life outcomes became insignificant after they controlled for 23 covariates in their specifications. However, including that many control variables has been criticized by other researchers (Orth and Robins, 2014). Another study by Baumeister, et al. (2003) argues that self-esteem is not a major predictor of educational and job performance. However, after that Baumeister and co-authors published their research, many studies have investigated the impacts of self-esteem on life outcomes and found self-esteem as a significant predictor of major life outcomes as well as educational and job success

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[13] Kautz et al. (2014), particularly argue that non-cognitive skills are more malleable than cognitive skills in adolescent years.

[14] Personality traits have been, to a high extent, considered heritable. Twin studies show that 40 to 60 percent of variation in non-cognitive skills and personality traits is due to genetic causes (Bouchard and Loehlin, 2001). Nevertheless, they are under influence of environment, family background, and years of schooling as well.

(Trzesniewski et al., 2006; Orth 2009; Orth et al., 2012; Kuster, et al, 2013; Marshall, et al, 2014). Also, in a review of the literature, Diener (1984) concludes that self-esteem is the most accurate predictor of life satisfaction in the United States, stronger than physical health, age, education, income, and marital status. In addition, Orth and Robins (2014) argue that self-esteem predicts success and well-being in health outcomes, job market, and relationships. They maintain that "Given the increasing evidence that self-esteem has important real-world consequences, the topic of self-esteem development is of considerable societal significance" (Orth and Robins 2014, P. 381).

The previous studies have discussed different ways that years of schooling can affect self-esteem[15]. For example, *social comparison* at school which refers to comparing own work with those of the peers, may positively or negatively affect self-esteem of the students. It is argued that social comparison serves several goals such as self-presentation, mastery, self-assessment, and self-enhancement (Taylor and Robel, 1989; Butler, 1989, Ruble and Frey, 1991; Pomerantz et al., 1995). Social comparison boosts the student's self-esteem if they realize that their work is more complete than that of their classmates. However, if the students come to the believe that they are less capable than their classmates then social comparison lowers their self-esteem (Pomerantz et al. 1995). Even, the damage to self-esteem of the students could be so serious that they might avoid it altogether. Brickman and Bulman (1977) argue that despite the fact that social comparisons may have a potential for self-enhancement, but it may be avoided because it can damage the self-esteem of own or others. For example, a student who looks at her classmate's work for self-assessment may be disappointed to know that she has accomplished far fewer homework assignments than her classmate. Also, a student who shows her finished work to her peers for the purpose of self-enhancement and realizes that they have not completed any of the assignment questions may feel embarrassed by her own superiority (Brickman and Bulman, 1977).

Besides social comparison, *school performance* has been discussed to affect self-esteem. For example, Skaalvik and Hagtvet (1990) find that good performance at school one year leads to a higher self-esteem the year after. Also, Rosenberg et al. (1989) find a causality relationship from

[15] Self-esteem improves from adolescence to about age 50 to 60 years-old when it peaks. Then, it begins to decline at an accelerating rate until old age. Even though self-esteem is immutable, it is also relatively stable. In addition, someone with a high self-esteem might go through a stage of low self-esteem after a decade and vice versa (Orth and Robins, 2014).

students' grades to self-esteem. They suggest that having a good performance at school make the students to think of themselves as capable at doing schoolwork, which can boost their self-esteem. Several studies find a correlation between school performance and self-esteem but it is worth noting that often they do not find any causality from self-esteem to school performance even though they find causality from performance to self-esteem (Rosenberg et al., 1989; Skaalvik and Hagtvet, 1990; Bowles, 1999; Baumeister et al., 2003). Other studies such as the one by Rubin et al. (1977) suggest that the correlation between academic performance and self-esteem is based on important underlying factors such as background and ability.

Another way that the impacts of years of schooling on self-esteem could be explained is through what that psychologists refer to as *contingency of self-worth*. Crocker and Wolfe (2001) define contingency of self-worth as "a domain or category of outcomes on which a person has staked his or her self-esteem, so that person's view of his or her value or worth depends on perceived successes or failures or adherence to self-standards in that domain" (Crocker and Wolfe 2001, P.594). They argue that families, institutions, and social groups have implicit or explicit criteria for what is valuable and worthwhile in people. For example, universities value academic achievements. Over time, these criteria internalize by individuals and they evaluate their own worth according to them (Crocker and Wolfe, 2001). Success in achieving goals relevant to one's contingencies of self-worth may boost her self-esteem. For example, students might believe being smart is what makes them worthwhile and so they try to get high grades because it shows that they are smart. Then, getting high grades improves their self-esteem. Also, when people believe a higher academic degree is what makes them worthwhile, receiving a higher academic degree may boost their self-esteem. However, people might have motivations that have little or nothing to do with contingency of self-worth. For example, a student might try to get high grades, or someone might try to receive a high academic degree only to facilitate landing a high paying job or to apply for a professional program (Crocker and Wolfe, 2001; Crocker et al. 2002).

Locus of control, the other non-cognitive skill measurement in this paper, also, has been positively associated with labor market outcomes (Heineck and Anger, 2010; Cobb-Clark, 2015; Caliendo et al., 2015). As an example, Heineck and Anger (2010) find that the external[16] locus of control is associated with a decrease in wages. Caliendo et al. (2015) also argue that individuals

[16] The meanings of internal and external locus of control are provided in Data and Identification Strategy section.

with a more internal locus of control scale search harder for jobs compared to the ones with a more external locus of control scale. Also, the individuals with internal locus of control scale have a stronger belief that investments in job search would pay off later. Individuals with external locus of control scale also have lower reservation wages[17] (Caliendo et al., 2015).

It has been discussed in the literature that one of the most influential interventions on locus of control is achieving a higher social status (Wolfle and Robertshaw, 1982). For example, Harvey (1971) maintains that upward mobility is associated with a change in locus of control toward internality. That means the individuals that experience an upward shift in their social status are likely to experience a change in their locus of control scale from external to internal levels. Education particularly can create a path toward a higher social status and has the potential to affect locus of control toward a more internal level. However, it is worth noting that studies such as the one by Wolfle and Robertshaw (1982) argue that the causal relationship between social status mobility and locus of control is a two-way street. Wolfle and Robertshaw (1982) emphasize that it is not surprising that new experiences, environments, and social conditions can lead to shifts in personality characteristics because those who experience a shift in their status might have a high degree of internal control at the first place. Therefore, part of the correlation between upward social status mobility and personality characteristics can be attributed to the same personality characteristics that affect social mobility. In a review of the literature, Pascarella and Terenzini (1991) provide ample evidence that locus of control increases during college education years (i.e. it becomes more internalized). However, Wolfle and Robertshaw (1982) suspect that the college students not only acquire higher education, but they are already internally oriented. Wolfle and Robertshaw (1982) argue that the strongest explanatory variable of locus of control among high school students is ability such that those with higher abilities have more internalized locus of control. However, Wolfle and List (2004) results show that even after controlling for ability, background, and previous levels of locus of control, college education affects locus of control of the students and shift it from external toward internal levels.

[17] Reservation wage is defined as the lowest wage that an employee accepts for a particular job.

Non-cognitive skills[18] are not limited to the Rosenberg Self-Esteem Scale[19] and Rotter Locus of Control Scale[20]. They include other skills as well. In this paper, we apply the Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale for the exact same reason that Heckman and his co-authors use them. As they point out, "we choose these measures because of their availability in the NLSY79" (Heckman et al. 2006, p. 429). Ideally, using a wider range of psychological measurements is preferable. Nevertheless, the Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale are two essential measurements of non-cognitive skills with significant educational and professional outcomes. Heckman et al. (2006) and other researchers such as Waddell (2006) and Deke and Haimson (2006) argue that Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale are associated with long term labor market outcomes.

Numerous studies point out the importance of non-cognitive skills on labor market outcomes (e.g. Gintis, 1971; Heckman and Rubinstein, 2001; Bowles, et al., 2001; Kuhn and Weinberger, 2005; Heckman et al., 2006; Waddell, 2006; Fortin, 2008; Deke and Haimson, 2006; Heineck and Anger, 2010; Dee and West, 2011; Drago, 2011; de Araujo and Lagos, 2013; Araujo and Lagos, 2013; Cobb-Clark, et al., 2015). A reasonable clue that shows the importance of non-cognitive skills in the job market comes from the behavior of the employers. In a survey of 400 employers in the U.S., Casner-Lotto and Barrington (2006) find that the top four skills that employers look for in applicants are oral communication, teamwork, work ethic and professionalism, and problem solving and critical thinking. Writing abilities, mathematics knowledge, and other cognitively demanding skills ranked lower than the mentioned soft skills. Self-esteem, one of the non-cognitive measurements that we use in this paper, has been associated with teamwork and higher levels of perseverance, two top soft skills that employers seek in job candidates (Murnane et al., 2001). Another finding of Murnane et al. (2001) is that there is a positive association between self-esteem and earnings 10 years later. Also, Gintis (1971) argues that if non-cognitive abilities are

[18] Note that psychologists and economists have used a variety of terminologies to describe non-cognitive skills. Other terms such as non-cognitive abilities, character skills, soft skills, socio-emotional skills, and personality traits have been used to refer to the same range of abilities or skills (Heckman and Kautz 2013; Garcia 2016). A well-known and widely accepted classification of personality traits (non-cognitive skills) is the "Big Five," which includes agreeableness, extraversion, neuroticism, conscientiousness, and openness to experience.

[19] Rosenberg Self-Esteem Scale measures an individual's subjective belief about her / his own worth. More details on how this scale is measured is provided in Appendix E.

[20] Rotter Locus of Control Scale measure the extend which individuals believe have control over their lives. More details on how this scale is measured is provided in Appendix F.

omitted in return to schooling specifications then the estimated impacts of education on earnings would be biased due to the impacts of non-cognitive abilities on earnings.

As mentioned before, in this paper, we apply a shift in aid policy that took place in 1982 to study the impacts of an exogenous variation in years of schooling on non-cognitive abilities including self-esteem and locus of control. Our results suggest that the impact of schooling on the Rosenberg Self-Esteem Scale and Rotter Locus of Control Scale is such that it improves self-esteem and increases sense of control over life (internal locus of control) when the previous levels of non-cognitive skills are not controlled for, but when those variables are included as control variable then the results are hardly statistically significant.

The rest of this paper is organized as follows. Section 2 explains the data and identification strategy. Section 3 outlines the empirical design of the paper. Section 4 provides the results, and Section 5 presents the conclusion of the study.

3.2 Data and Identification Strategy

3.2.1 Data

NLSY79 is a nationally representative sample of 12,686 young American men and women aged between 14 and 22 years when they were first surveyed in 1979. After 1979, the data has been collected in most of the years until 2016. Table 20 represents the number and percentage of each gender, and ethnic group represented in NLSY79.

Table 20. Characteristics of NLSY79 dataset

	Number	Percentage
Total	12,686	100
Hispanic	2,002	15.78
Blacks	3,174	25.02
Non-Hispanic & Black	7,510	59.19
Males	6,403	50.47
Females	6,283	49.53

We use the Rosenberg Self-Esteem Scale, which is designed by Rosenberg (1965), as one of the measurements of non-cognitive ability. NLSY79 provides the Rosenberg Self-Esteem Scale in the 1980, 1987, and 2006 interviews. In this scale, the respondents are asked to express their opinions regarding 10 statements of self-approval and disapproval. The respondents are asked to pick one of the options among strongly agree, agree, disagree, or strongly disagree. An example of a Rosenberg Self-Esteem Scale statement is “I am a person of worth.” A higher score indicates higher self-esteem. Please see Appendix E for more details on the Rosenberg Self-Esteem Scale, including the questions that are asked from the participants, the number of participants, and the scores.

The other variable that we use as a measurement of non-cognitive skills is the Rotter Locus of Control Scale designed by Rotter (1966). The NLSY79 provides Rotter Locus of Control Scale in 1979 and 2014. This variable measures the extent that individuals believe they have control over their lives, which can be explained as internal control versus external control. Internal control is about the extent by which individuals believe they have control over their lives through self-motivation or self-determination, while external control is about the extent that they believe the environment (that is, chance, fate, luck, etc.) controls them. Higher scores indicate that the individual is more external. However, in this paper, we reverse the sign of locus of control scores, so the results are consistent with those of the self-esteem coefficients.

Note that we standardize self-esteem and locus of control scales such that their means equal to zero and their standard deviations set to one. This enables us to intemperate the impacts of education on the mentioned scales in percentage points.

3.2.2 Identification Strategy

Studying the impacts of education on abilities is a challenge because improvement in abilities could improve education as well. In addition, unobserved variables that might affect both education and abilities contribute to the endogeneity of education. Therefore, due to the endogeneity of education, the estimated impacts of education on ability would be biased. Nevertheless, exogenous variation in years of schooling helps to overcome the problem of endogeneity of education. To overcome this issue, we need a source of variation in schooling that is exogenous to unobservable variables that might influence non-cognitive abilities. In this paper, we apply a shift in aid policy that affects the school attendance of some students but not all of them to study the impacts of schooling on non-cognitive abilities. The policy that we apply is the elimination of a Social Security student benefit program in 1982.

From 1965 to 1982, the Social Security Administration provided aid for the 18 to 22 years old children of Social Security beneficiaries, including the children of deceased, disabled, and retired parents. Prior to 1965, aid was provided to the children of Social Security beneficiaries only up to age 18. From 1965 to 1982, the Social Security Administration covered students up to age 22 if they were full time college students. According to the data from National Center for Education Statistics, the program covered 700,000 college students at its peak. From 1977 to 1982, the number of covered students dropped moderately to 600,000 due to a national drop in college enrolment rates in the U.S. (Dynarski, 2003). In 1981, Congress voted to eliminate the Social Security student benefit program. Students who were not enrolled in college by May 1982 were no longer eligible to receive aid. Moreover, payments to the ones who were enrolled in college were significantly reduced.

Since parental retirement and disability could be endogenous due to availability of student benefits, we apply eligibility for aid due to death of the parent in this paper. Following Dynarski (2003), we focus on the students with deceased fathers since 90 percent of the students were eligible for the program from that cause. Note that the focus of the paper is estimating the impacts of *aid eligibility* on education and non-cognitive abilities rather than estimating the impacts of *aid receipt* on the mentioned variables. This approach enables us to unbiasedly predict the impact of eliminating the aid policy because the policy makers control the offer of the aid but not its take up.

Table 21 shows the mean and standard error of the education level of the students with deceased and not deceased father before and after the policy change. The variable *complete college by age 23* is a binary variable that sets one if an individual completed any years of college by age 23. Otherwise, it is equal to zero. *complete college by age 28* equals to one if a person completed any years of college before age 28. *schooling by age 23* is the number of years of schooling that a person has completed by age 23. In addition, for each variable in Table 21, the number of observations is provided underneath the mean and standard error. Standard errors are in parentheses. The mean of all the variables in the table show that children of deceased fathers are better off in terms of education before the change in policy in 1982. For example, their years of schooling by age 23 which has been 13 and larger than that of other students has decreased to 12.7 while years of schooling of the regular students has increased. The last column of Table 21 shows the difference-in-differences impact of eligibility for Social Security student benefits on educational outcomes. The positive means in the last column show the positive impact of the student eligibility for the Social Security student aid program on education outcomes. Standard errors in this column are clustered by household due to presence of siblings in some families. Table

21 provides some suggestive evidence for the difference-in-differences findings and the results in this table will be tested.

Table 21. NLSY Summary Statistics

	High school seniors 1979-1981		**High school seniors 1982-1983**		
	Father Not deceased	**Father deceased**	**Father Not deceased**	**Father deceased**	**Difference-in-Differences**
schooling by age 23	12.839	13	12.852	12.702	0.309
	(0.050)	(0.090)	(0.095)	(0.175)	(0.215)
Number of obs.	699	247	210	74	1,230
complete college by age 23	0.372	0.425	0.394	0.358	0.089
	(0.018)	(0.031)	(0.033)	(0.054)	(0.071)
Number of obs.	716	256	218	81	1,271
complete college by age 28	0.461	0.505	0.552	0.419	0.177
	(0.019)	(0.031)	(0.034)	(0.055)	(0.074)
Number of obs.	722	257	219	81	1,279

Note: Schooling by age 23 is the number of years of schooling that an individual has completed by age 23. Complete college by age 23 is a binary variable that equals to one if an individual has completed any years of college by age 23. Otherwise, it is equal to zero. complete college by age 28 equals to one if a person completed any years of college by age 28. Otherwise, it is equal to zero.

3.3 Empirical Design

We apply the difference-in-differences approach to study the impacts of eligibility for Social Security benefits on educational outcomes. To do so, we estimate the following standard difference-in-differences model:

$$Schooling_i = \beta_1 + \beta_2(father\ deceased_i \times before_i) + \beta_3 father\ deceased_i + \beta_4 before_i + \beta_5 X_i + \epsilon_i \qquad (11)$$

where $Schooling_i$ stands for educational outcomes for individual i. In the empirical results section of the paper, when we show the results, we clarify what exactly $Schooling_i$ stands for in each estimated regression. *father deceased* is a binary variable that is equal to one for those who are potentially eligible for Social Security student benefits due to death of their fathers. Also $before_i$, is a binary variable that shows that individual i graduated from high school before the elimination of the program. $before_i$ equals to one if individual i is a high school senior in 1979, 1980, or 1981. The NLSY79 dataset that we use starts in 1979. Therefore, we do not have data prior to 1979. $before_i$ is zero if individual i is a high school senior in 1982 or 1983 (i.e. after elimination of the program). The reason that high school seniors after 1983 are not included in our regressions is that they age out of the 18-22 years old eligibility for the program. X_i represents a vector of family background control variables and birth year and region fixed effects.

Since the literature discusses that schooling could be endogenous due to unobserved innate ability, we apply instrumental variables specifications to address this issue. In a regular least square specification that aims to estimate the impacts of education on labor market outcomes, innate ability is in the error term and might be correlated with the dependent variable.

We are interested in understanding the impacts of years of schooling on non-cognitive skills (i.e. Rosenberg Self-Esteem Scale and Rotter Locus of Control Scale). This relationship can be specified as follows:

$$Y_i = \delta_1 + \delta_2 Schooling_i + \delta_3 father\ deceased_i + \delta_4 before_i + \delta_5 X_i + \epsilon_i \quad (12)$$

where Y_i is the outcome variable for individual *i*. The outcome variable in our regressions is either Rosenberg Self-Esteem Scale or Rotter Locus of Control Scale. The rest of the variables are introduced before.

We apply the interaction between *father deceased* and *before* as an instrument in the following model, which serves as the first stage of our two-stage least-square specification for equation 12:

$$Schooling_i = \theta_1 + \theta_2(father\ deceased_i \times before_i) + \theta_3 father\ deceased_i + \theta_4 before_i + \theta_5 X_i + \omega_i \quad (13)$$

where all the variables are introduced in equations 11 and 12. The interaction of *father deceased* and *before* is an exogenous variable that affects years of education but does not affect noncognitive abilities directly.

3.4 Empirical Results

In this section, Table 22 provides the estimates of the difference-in-differences model (i.e. equation 11) and Tables 23 to 26 present the estimates of the least-square and the two-stage least-square models (i.e. equations 12 and 13). The goal of Tables is to estimate the impacts of aid eligibility on schooling. This helps us to realize whether the elimination of the Social Security student benefits causes any variations in schooling outcomes. In Tables 23 and 24, the least-square methodology is applied to estimate the impacts of schooling on non-cognitive abilities. As discussed before, the results from least-square estimations could be biased due to the possible endogeneity of schooling. Therefore, in Tables 25 and 26, the two-stage least-square estimations that apply instrumental variables to control for endogeneity of schooling are provided. The two-stage least-square regressions estimate the impacts of variation in years of schooling on non-cognitive abilities.

In Table 22 the results for the main difference-in-differences model is estimated with either no control variables or a full set of control variables. Note, that Appendix G provides estimates of the difference-in-differences model with four different subset of control variables. Note that in Table 22 age squared is age powered by two and shows the sensitivity of the results to the functional form of the regression taken by age. Also, Nonsmsa is a binary variable that sets to one if individual *i* does not live in a city, and it is zero otherwise. Centrsmsa is a binary variable that equals to one if individual *i* lives in the central city. Zasvab is the standardized ASVAB score of individual *i*, The ASVAB includes 10 tests that measure skill and knowledge in general science, arithmetic reasoning, paragraph comprehension, word knowledge, coding speed, numerical operations, mathematics knowledge, auto and shop information, electronics information, and mechanical comprehension. A standardized ASVAB score has been added to our covariates to control for skills, knowledge, and cognitive abilities of the participants. Region of birth refers to one of the four regions in the United States: Northeast, the Midwest, the South, and the West. All covariates x before is the interaction of all covariates by *before*. This controls for heterogeneity across eligibility status and time. For example, this interaction term absorbs the changes in economy that might affect family income and therefore school attendance of the youth.

Table 22 represents the impact of eligibility for student benefits on years of schooling by age 23, complete college by age 23, and complete college by age 28. Note that schooling is not a binary variable, but it is the actual years of schooling. However, complete college by age 23 and 28 are binary variables. The results show positive impact of eligibility for student benefits on years of schooling and completing any years of college. That means that eligibility for student benefits is associated with almost half a year increase in schooling per person. Please see Appendix G for more details.

Table 22. Impact of eligibility for Social Security student benefits on education

	schooling by age 23		**complete college by age 23**		**complete college by age 28**	
father deceased x before	0.309	0.491*	0.089	0.238**	0.177**	0.293***

	(0.215)	(0.259)	(0.071)	(0.085)	(0.074)	(0.088)
father deceased	-0.149	-0.348	-0.036	-0.180**	-0.132**	-0.257***
	(0.199)	(0.235)	(0.063)	(0.075)	(0.064)	(0.078)
before	-0.012	0.311	-0.021	-0.503**	-0.091**	-0.118
	(0.107)	(0.884)	(0.037)	(0.244)	(0.038)	(0.295)
family income		Y		Y		Y
black		Y		Y		Y
Hispanic		Y		Y		Y
father attended college		Y		Y		Y
mother attended college		Y		Y		Y
single parent family		Y		Y		Y
family size		Y		Y		Y
age88		Y		Y		Y
female		Y		Y		Y
age^2		Y		Y		Y
married		Y		Y		Y
nosmsa		Y		Y		Y
centrsmsa		Y		Y		Y
Zasvab		Y		Y		Y
Year of birth fixed effect		Y		Y		Y
Region fixed effect		Y		Y		Y
All covariates x before		Y		Y		Y
Number of obs.	1,230	875	1,279	884	1,279	884
R-squared	0.003	0.189	0.046	0.171	0.005	0.177

Note: Schooling by age 23 is the number of years of schooling that an individual has completed by age 23. Complete college by age 23 is a binary variable that equals to one if an individual has completed any years of college by age 23. Otherwise, it is equal to zero. complete college by age 28 equals to one if a person completed any years of college by age 28. Otherwise, it is equal to zero.

Family income is the income of the family that individual *i* has grown up there. Black is a binary variable that set to one if individual *i* is black and it is zero otherwise. Hispanic is one if individual *i* is Hispanic and it is zero otherwise. Father and mother attended college are binary variables that show parents of individual *i* have attended college. Single parent is a binary variable that equals to one if individual *i* has grown up in a single parent household and it equals to zero otherwise. Family size refers to actual number of the family members. Female is a binary variable that sets to one if individual *i* is a female and it is zero otherwise. Age squared is age powered by two. Married, is a binary variable and shows whether a person is married or single. Nonsmsa sets to one if individual *i* does not live in a city, and it is zero otherwise. Centrsmsa equals to one if individual *i* lives in the central city. Zasvab is the standardized ASVAB score of individual *i*, Region of birth refers to one of the four regions in the United States: Northeast, the Midwest, the South, and the West. All covariates x before is all covariates multiplied by *before*.

The upper numbers in each column show the coefficient of the independent variable provided in the first column (i.e. column in the left) of the table. The numbers in parentheses represent standard errors. Y means that the associated covariate is included in the estimation of the equation. All regressions are clustered at the household level. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

As mentioned before, the goal of this paper is to understand the impacts of schooling on non-cognitive abilities rather than the impacts of aid on schooling. Dynarski (2003) studied the impacts of variation in aid on years of schooling and college attendance. Here, not only we replicated her results and found similar impacts of aid on education, but we provided more details on the impacts of aid eligibility on schooling. Our findings to this point give us confidence that we have estimated the impacts of eligibility for Social Security student benefits on schooling correctly. Moreover, our results assure us that the variation in aid eligibility has created a significant variation in college attendance and years of schooling. We apply this variation in our 2SLS specifications to estimate the impacts of years of education on non-cognitive abilities. However, before discussing the 2SLS results we have presented the results of least-square estimations.

Table 23 shows the results of the least-square estimations of equation 2. The upper numbers in each cell under columns (1) to (6) show the coefficient of schooling by age 23. The numbers in parentheses represent standard errors. Column (1) is estimated without any control variables. The covariates in column (2) include family Income, black, Hispanic, father attended college, mother attended college, single parent, family size, age, and female. The covariates in column (3) include all of those in column (2) and age powered by 2. In column (4), all covariates of column (3) and four new covariates, including married, nosmsa, centrsmsa, and standardized ASVAB test scores are added to the regressions. In column (5), all covariates in column (4) and year of birth and region of birth fixed effects are added. In column (6), all covariates in column (4) and the interaction of all of covariates with *before* are included.

The first row in the table shows the impacts of schooling by age 23 on the standardized Rosenberg Self-Esteem Scale that is measured in 1987. Note that, in 1987, the youngest participants in NLSY 1979 dataset are 23 years old. The results show that the impact of years of schooling by age 23 on the standardized Rosenberg Self-Esteem Scale measured in 1987 is positive and relatively stable in columns (1) to (6). The impacts vary from 12.7 to 14.0 percentage points.

The second row shows the impact of years of schooling completed by age 23 on the standardized Rosenberg Self-Esteem Scale measured in 2006. In 2006, the youngest participant in NLSY dataset is 42 years old. Hence, other than some rare exceptions, everybody should be out of school by 2006. Here, the coefficients are smaller compared to those in the first row and we still see some positive impacts of years of schooling on the Rosenberg Self-Esteem Scale measured in 2006 when the participants ages range from 42 to 49.

The last row in Table 23 represents the impacts of schooling by age 23 on the Standardized Rotter Locus of Control Scale measured in 2014. As can be seen, the coefficients in all three rows are positive, which means more years of schooling is associated with an increase in the sense of control over life (positive impacts on internal locus of control and negative impacts on external locus of control). The impacts of years of schooling by age 23 on the Standardized Rotter Locus of Control Scale varies between 7.2 and 9.5 percentage points.

In addition, Table 24 represents the impacts of complete any years of college by age 23 on the standardized Rosenberg Self-Esteem Scale measured in 1987 and 2006 and standardized Rotter Locus of Control Scale measured in 2014. The results show positive impacts of complete any years of college by age 23 on non-cognitive abilities.

Table 23. Impact of education on non-cognitive skills – least-square estimations. Independent variable of interest: schooling by age 23

Dependent variable	(1)	N. of obs.	R2	(2)	N. of obs.	R2	(3)	N. of obs.	R2	(4)	N. of obs.	R2	(5)	N. of obs.	R2	(6)	N. of obs.	R2
Z. Rosenberg 1987	0.135*** (0.019)	1,173	0.045	0.127*** (0.023)	869	0.069	0.127*** (0.023)	869	0.071	0.136*** (0.023)	869	0.082	0.127*** (0.023)	858	0.090	0.140*** (0.023)	858	0.140
Z. Rosenberg 2006	0.064*** (0.022)	883	0.011	0.050* (0.027)	640	0.038	0.050* (0.027)	640	0.039	0.054* (0.028)	640	0.042	0.050* (0.027)	631	0.071	0.048 (0.029)	631	0.118
Z. Rotter 2014	0.095*** (0.024)	760	0.021	0.072** (0.031)	557	0.041	0.073** (0.031)	557	0.041	0.079** (0.031)	557	0.050	0.076* (0.031)	549	0.060	0.075** (0.031)	549	0.146

Note: The upper numbers in columns (1) to (6) show the coefficient of schooling by age 23.

Column (1) include no control variables. Column (2) includes father deceased, before, family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age88, and female. Column (3) includes all the covariates in column (2) and age powered by 2. Column (4) includes all the covariates in column (3) and married, nosmsa, centrsmsa, Zasvab. Column (5) includes all the covariates in column (4) and year of birth and region fixed effect. Column (6) includes all the covariates in column (5) and the interaction of all covariates and *before*.

Family income is the income of the family that individual i has grown up there. Black is a binary variable that set to one if individual i is black and it is zero otherwise. Hispanic is one if individual i is Hispanic and it is zero otherwise. Father and mother attended college are binary variables that show parents of individual i have attended college. Single parent is a binary variable that equals to one if individual i has grown up in a single parent household and it equals to zero otherwise. Family size refers to actual number of the family members. Female is a binary variable that sets to one if individual i is a female and it is zero otherwise. Age squared is age powered by two. Married, is a binary variable and shows whether a person is married or single. Nonsmsa sets to one if individual i does not live in a city, and it is zero otherwise. Centrsmsa equals to one if individual i lives in the central city. Zasvab is the standardized ASVAB score of individual i, Region of birth refers to one of the four regions in the United States: Northeast, the Midwest, the South, and the West. All covariates x before is all covariates multiplied by *before*.

The numbers in parentheses represent standard errors. N. of obs. represents number of observations. R2 stands for R squared. All regressions are clustered at the household level. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 24. Impact of education on non-cognitive skills – least-square estimations. Independent variable of interest: complete college by age 23

Dependent variable	(1)	N. of obs.	R2	(2)	N. of obs.	R2	(3)	N. of obs.	R2	(4)	N. of obs.	R2	(5)	N. of obs.	R2	(6)	N. of obs.	R2
Z. Rosenberg 1987	0.381*** (0.054)	1,188	0.045	0.362*** (0.064)	876	0.070	0.362*** (0.064)	876	0.070	0.362*** (0.064)	876	0.072	0.386*** (0.065)	876	0.083	0.366*** (0.065)	865	0.092
Z. Rosenberg 2006	0.169*** (0.058)	898	0.010	0.160** (0.072)	646	0.038	0.163** (0.072)	646	0.040	0.170** (0.073)	646	0.042	0.154** (0.073)	637	0.072	0.143* (0.078)	637	0.113
Z. Rotter 2014	0.306*** (0.066)	774	0.027	0.324*** (0.083)	562	0.056	0.326*** (0.083)	562	0.057	0.339*** (0.083)	562	0.065	0.329*** (0.084)	554	0.075	0.315*** (0.086)	554	0.156

Note: The upper numbers in columns (1) to (6) show the coefficient of complete college by age 23.

Column (1) include no control variables. Column (2) includes father deceased, before, family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age88, and female. Column (3) includes all the covariates in column (2) and age powered by 2. Column (4) includes all the covariates in column (3) and married, nosmsa, centrsmsa, Zasvab. Column (5) includes all the covariates in column (4) and year of birth and region fixed effect. Column (6) includes all the covariates in column (5) and the interaction of all covariates and *before*.

Family income is the income of the family that individual i has grown up there. Black is a binary variable that set to one if individual i is black and it is zero otherwise. Hispanic is one if individual i is Hispanic and it is zero otherwise. Father and mother attended college are binary variables that show parents of individual i have attended college. Single parent is a binary variable that equals to one if individual i has grown up in a single parent household and it equals to zero otherwise. Family size refers to actual number of the family members. Female is a binary variable that sets to one if individual i is a female and it is zero otherwise. Age squared is age powered by two. Married, is a binary variable and shows whether a person is married or single. Nonsmsa sets to one if individual i does not live in a city, and it is zero otherwise. Centrsmsa equals to one if individual i lives in the central city. Zasvab is the standardized ASVAB score of individual i, Region of birth refers to one of the four regions in the United States: Northeast, the Midwest, the South, and the West. All covariates x before is all covariates multiplied by *before*.

The numbers in parentheses represent standard errors. N. of obs. represents number of observations. R2 stands for R squared. All regressions are clustered at the household level. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Tables 25 and 26 show the two-stage least-square estimations of equation 3. We have used the interaction of *father deceased* and *before* as an instrument. This instrument has good explanatory power in the first stage. Note that using the interactions between *father deceased* and *after* as an instrument produces exact same results with the same sign as that of the interaction of *father deceased* and *before*. In Table 25 the instrumented variable is schooling by age 23 and in Table 26 the instrumented variable is completed any years of college by age 23. Note that appendix H provides the results of the two-stage least-square estimates with different subsets of control variables.

The dependent variable in Table 25 is standardized Rosenberg Self-Esteem Scale that is measured in 1987. The results are presented in two rows. In the first row the previous levels of non-cognitive abilities are not controlled for, but in the second row they are controlled for.

Perhaps the most important aspect of the results in Tables 25 and 26 is that education has a significant impact on non-cognitive skills when we do not control for a previous level of non-cognitive skill, but when the previous levels of non-cognitive skills are controlled for we hardly see any significant impact. In Tables 25 and 26 when a previous level of self-esteem is not included as a control variable, we can see a significant and positive impact of education on self-esteem and when a previous measure of self-esteem is included as a control variable, the impacts are still positive, but they are either are not statistically significant or they are significant at 10 percent level. The impact of education on locus of control is positive and statistically significant at 10 percent level when a previous level of locus of control is not controlled for, but when it is added as control variable the impact is not statistically significant, but the coefficients stay positive. That means the impact of education is such that it shifts locus of control from external to internal levels, but the impact is hardly statistically significant.

Table 25. Impact of education on non-cognitive skills – two-stage least-square estimations. Instrumented variable: schooling by age 23

Independent variable	Z. Rosenberg 1987	Z. Rosenberg 2006	Z. Rotter 2014
Coefficient of schooling by age 23	0.269** (0.105)	0.245** (0.100)	0.274* (0.158)
Number of obs.	896	667	576
Test of weak instruments: first stage F	11.933	11.297	14.960
Previous non-cognitive measure as a control variable	NO	NO	NO
Coefficient of schooling by age 23	0.115 (0.114)	0.189* (0.110)	0.262 (0.165)
Number of obs.	895	666	573
Test of weak instruments: first stage F	9.435	9.350	14.143
Previous non -cognitive measure as a control variable	Z. Rosenberg 1980	Z. Rosenberg 1980	Z. Rotter 1979

Instrumented: schooling by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables: family income, age, and standardized ASVAB score
All regressions are clustered at the household level.
The numbers in parentheses represent standard errors.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 26. Impact of education on non-cognitive skills – two-stage least-square estimations. Instrumented variable: complete any years of college by age 23

Independent variable	Z. Rosenberg 1987	Z. Rosenberg 2006	Z. Rotter 2014
Coefficient of complete college by age 23	0.918** (0.378)	0.907** (0.360)	0.928* (0.489)
Number of obs.	905	676	581
Test of weak instruments: first stage F	9.761	9.308	8.808
Previous non -cognitive measure as a control variable	NO	NO	NO
Coefficient of complete college by age 23	0.351 (0.426)	0.700* (0.401)	0.850* (0.471)
Number of obs.	904	675	562
Test of weak instruments: first stage F	7.023	7.142	11.746
Previous non -cognitive measure as a control variable	Z. Rosenberg 1980	Z. Rosenberg 1980	Z. Rotter 1979

Instrumented: complete any years of college by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables: family income, age, and standardized ASVAB score
All regressions are clustered at the household level.
The numbers in parentheses represent standard errors.
*: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

3.5 Conclusion

Understanding the true impacts of college education on non-cognitive skills remains as a highly crucial question in the literature because the previous studies have not paid enough attention to this question despite the fact that they have highlighted the importance of non-cognitive skills. Multiple studies argue that non-cognitive skills are highly important in daily life and they have crucial life and professional outcomes. For example, Diener (1984) finds self-esteem as the strongest predictor of life satisfaction in the United States, stronger than physical health, age, education, income, and marital status. Nevertheless, the previous studies do not offer a clear picture of the impacts of education on non-cognitive skills. Heckman et al. (2013) finds positive impacts of education on non-cognitive abilities of 3 to 4 years-old children and Dee and West (2011) finds out that reduction in the 8th grade class sizes in Germany improves non-cognitive skills. But, does college education have positive impacts on non-cognitive skills as Heckman et al. (2013) and Dee and West (2011) find for children in younger ages? Kautz et al. (2014), argue that non-cognitive skills are malleable in adolescent years and they are influenced by schooling. However, Bachman et al. (1978) maintain that college education has little or no impact on self-esteem. Bachman et al. (1978) find that educational attainment does not affect self-esteem when previous levels of self-esteem are controlled for and Wolfle and Robertshaw (1982) reach an identical finding about locus of control. Wolfle and Robertshaw's (1982) results show that education beyond high school does not significantly affect locus of control. Nevertheless, Pascarella and Terenzini (1991) maintain that locus of control improves during college education years and becomes more internalized, but Wolfle and Robertshaw (1982) suspect that the college students are already internally oriented. They argue that the strongest explanatory variable of locus of control among high school students is ability such that those with higher abilities have more internalized locus of control. However, Wolfle and List (2004) results show that even after controlling for ability, background, and previous levels of locus of control, college education affects locus of control of the students and shift it from external toward internal levels.

We apply NLSY79 that contains data from over 12,000 young Americans to study the impacts of college education in the United States on non-cognitive abilities. Since schooling is an endogenous variable, variation in the years of schooling that is exogenous to unobservable variables that might influence non-cognitive abilities is essential to overcome the problem of endogeneity of schooling. In this paper, we apply a shift in aid policy that affects school attendance of a portion of students but not all of them to capture exogenous variations in years of schooling. The policy that we apply is the elimination of a Social Security student benefits program in 1982 that from 1965 to 1982 provided aid for the children of Social Security beneficiaries aged 18 to 22.

Note that the focus of the paper is to estimate the impacts of aid eligibility on educational outcomes and non-cognitive abilities rather than the impacts of aid receipt on education and non-cognitive abilities. Also, we focus on eligibility for aid due to the death of father. 90 percent of the students were eligible for the program because of the death of their fathers. In our two-stage least-square estimations, we have used the interaction of *father deceased* and *before* as an instrument. The interaction of *father deceased* and *before* is an exogenous variable that affects years of education but does not directly affect noncognitive abilities. *father deceased* is a binary variable that indicates if the father is deceased, and *before* is another binary variable that shows that a student has been a high school senior in the years 1979, 1980, and 1981versus years 1982 and 1983.

Our difference-in-differences results show a positive impact of eligibility for student benefits on years of schooling and completing any years of education at college.

The results of the two-stage least-square estimations show that education has a significant impact on non-cognitive skills when the previous levels of non-cognitive skills are not controlled for, but when we control for the previous levels of non-cognitive skills then we hardly see any statistically significant impacts of education on non-cognitive skills. The results show that when a previous level of self-esteem is not included as a control variable, the impact of education on self-esteem is significant and positive, but when a previous level of self-esteem is included as a control variable, even though the impacts are still positive, but they are not statistically significant in most cases.

The results from the two-stage least-square estimations show parallel findings for the impacts of education on locus of control. In most cases, when previous levels of locus of control are included the statistically significance level of the coefficients decreases. The coefficients stay positive in all estimations which suggest that locus of control shifts from external to internal levels during college years.

Note that the results of this paper do not entirely deny the positive impacts of formal college education on non-cognitive abilities. In fact, we also find positive impacts, but when we control for the previous levels of non-cognitive skills, we rarely see any significant impact. Hence our results are in line with the findings of Wolfle and Robertshaw (1982) and Pascarella and Terenzini (1991) who found similar results decades ago. As mentioned before, several scholars report positive impacts of education on non-cognitive skills which is a different finding from that of Wolfle and Robertshaw (1982) and Pascarella and Terenzini (1991), but our results do not confirm any causality relationship from college education to non-cognitive skills. The results of this paper confirm that the Social Security student aid program had positive and significant impacts on educational outcomes, including length of education and college attendance. However, despite the fact that the impacts of education on non-cognitive skills are positive, but they are not significantly different from zero.

Note that we do not deny the potential positive impacts of the Social Security student aid program on the life and professional outcomes of the beneficiary students. We find positive impacts of the program on education attainment and the program possibly had other positive impacts that could be investigated in the future studies. Also, note that this paper does not provide any cost-benefit analysis of the Social Security student aid program. In addition, the sample used in this paper, which includes the children of Social Security beneficiaries at high school and college age, might not represent all American students at all levels of education. However, we believe that these results are replicable for samples of students that are more representative of the population of American college students.

APPENDICES

APPENDIX A

Hospital beds per head in treated countries:

country	ccd
Yemen	1
Syria	2
Iraq	3
Iran	4
Oman	5
UAE	6
Saudi	7
Qatar	8
Algeria	9
Kuwait	10
Bahrain	11
Libya	12
All	13
Treated	14
Control	15

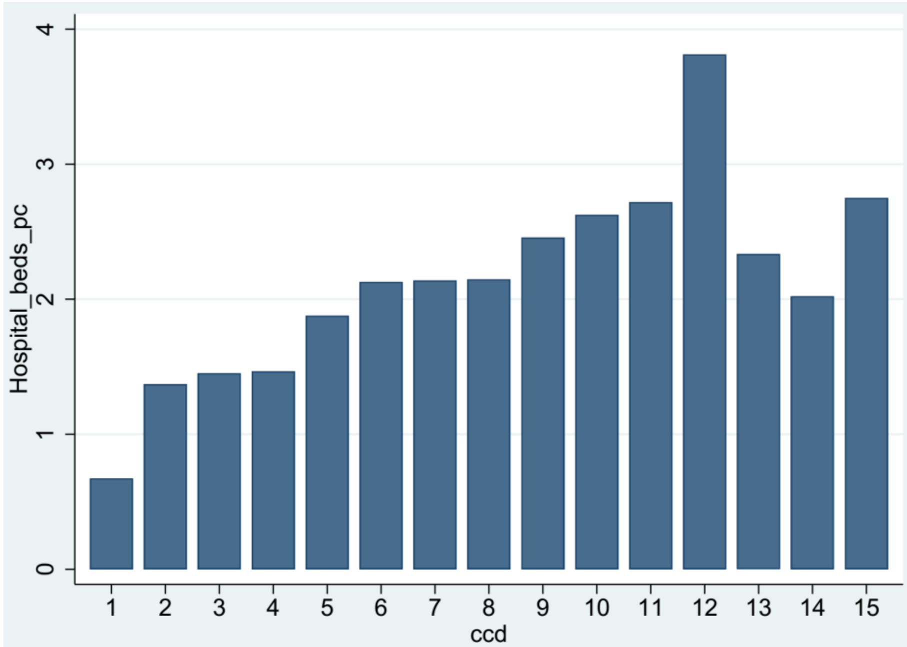
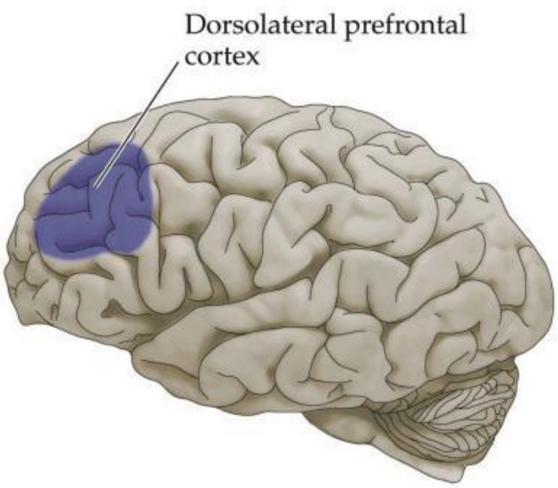


Figure 11. Number of hospital beds per head in each treated country

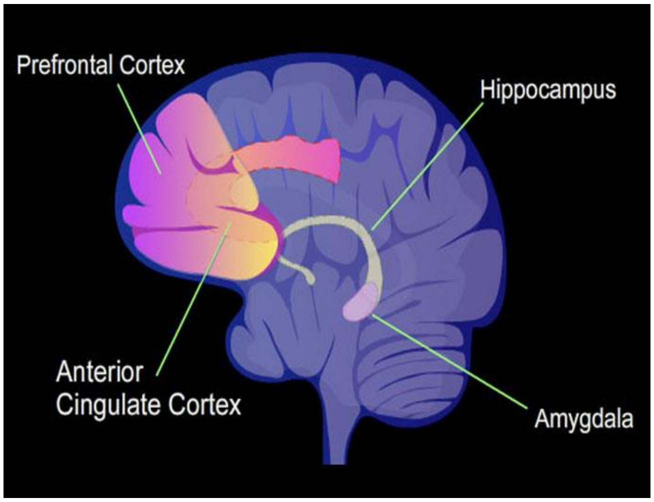
The two columns in the left side of the figure show the country code (ccd) associated with each country.

APPENDIX B

Dorsolateral prefrontal cortex, anterior cingulate cortex, and the hippocampus.



A.



B.

Figure 12. Dorsolateral prefrontal cortex, anterior cingulate cortex, and the hippocampus

A and B show dorsolateral prefrontal cortex, anterior cingulate cortex, and the hippocampus in the brain. Fluid intelligence relies on function of the anterior cingulate cortex and dorsolateral prefrontal cortex, while crystallized intelligence is dependent on the function of the hippocampus.

Source of image in Figure 13.A is https://www.sicotests.com/psyarticle.asp?id=191

Source of image in Figure 13.B is National Institute of Mental Health

APPENDIX C

Figure 13 Shows the coverage of Indonesian Family Life Survey (IFLS) in Indonesia. Figure 15 Represents the density of the INPRES program from 1973 to 1978. The darker colors show that number of constructed INPRES schools per 1,000 children is greater than the lighter ones.

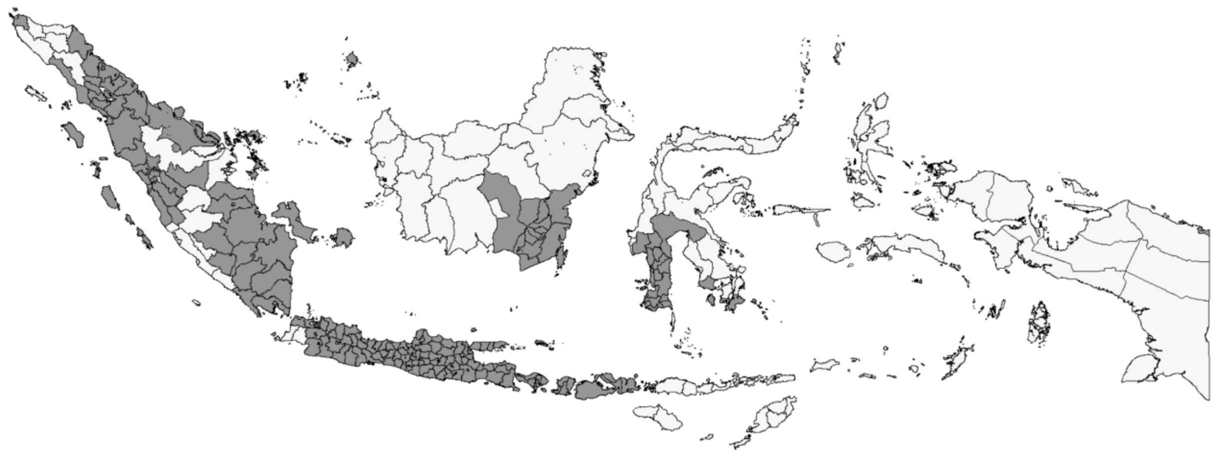


Figure 13. Indonesian Family Life Survey (IFLS) on map of Indonesia

Districts in gray are covered by Indonesian Family Life Survey (IFLS).

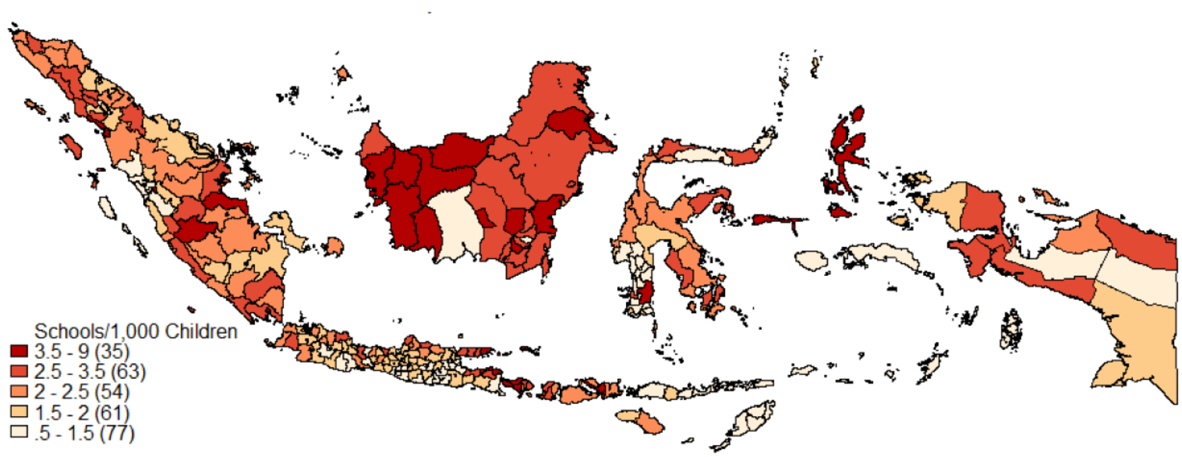
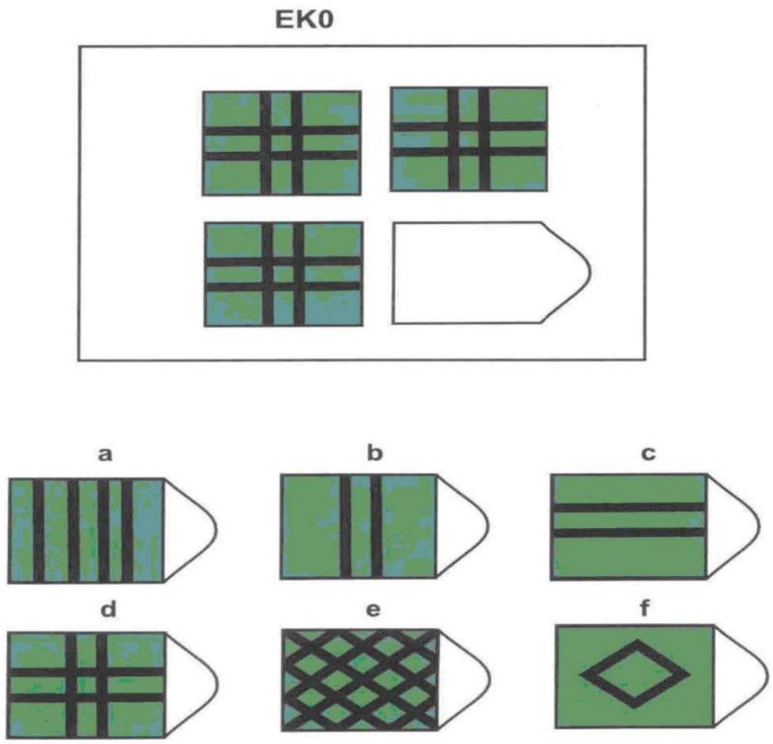


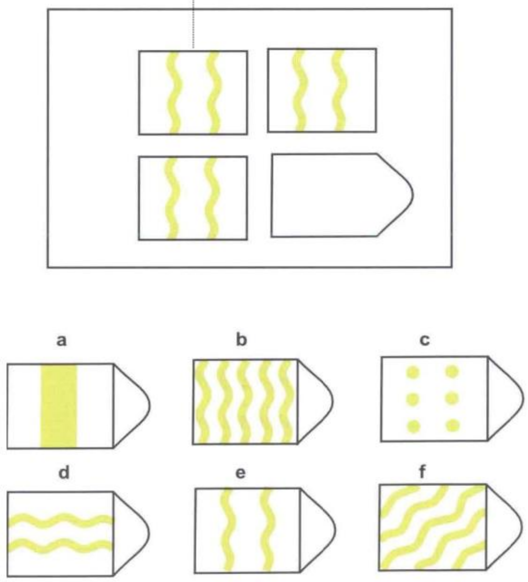
Figure 14. Intensity of the INPRES program from 1973-1978 on map of Indonesia

APPENDIX D

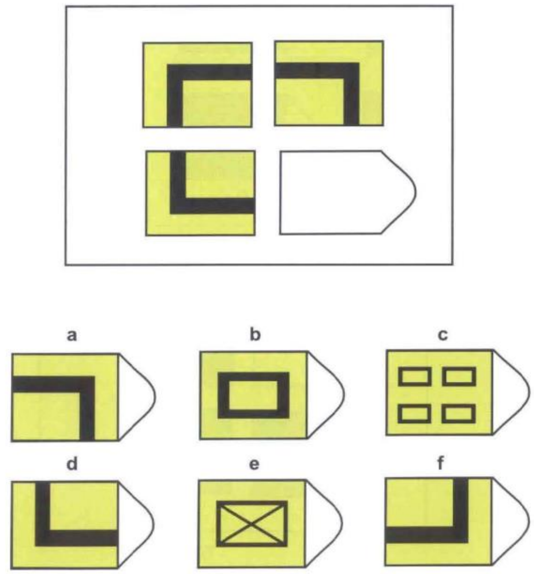
The followings are the Raven Progressive Matrices (RPM) that are used in the Indonesian Family Life survey (IFLS).



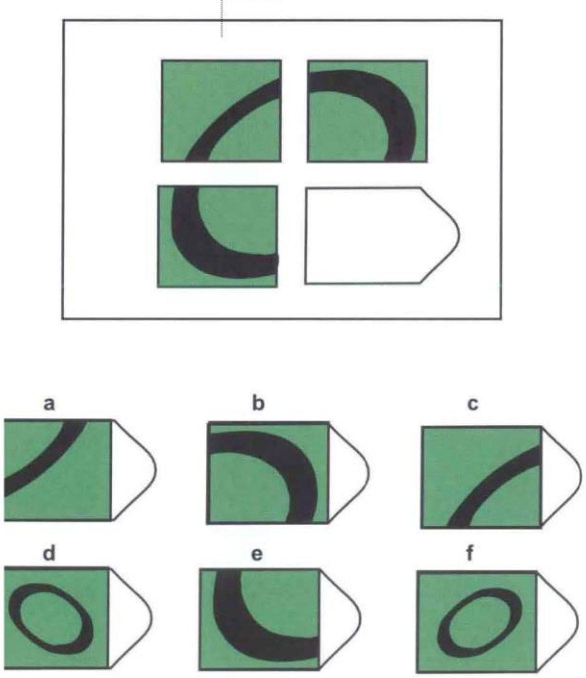
EK1



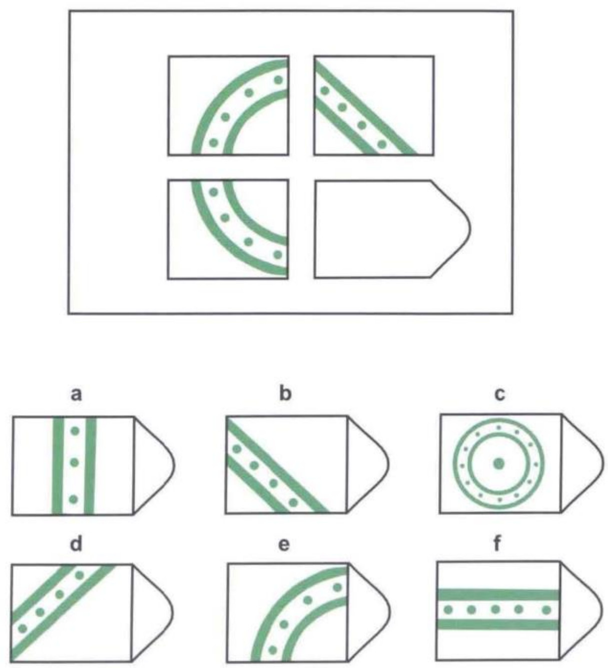
EK2



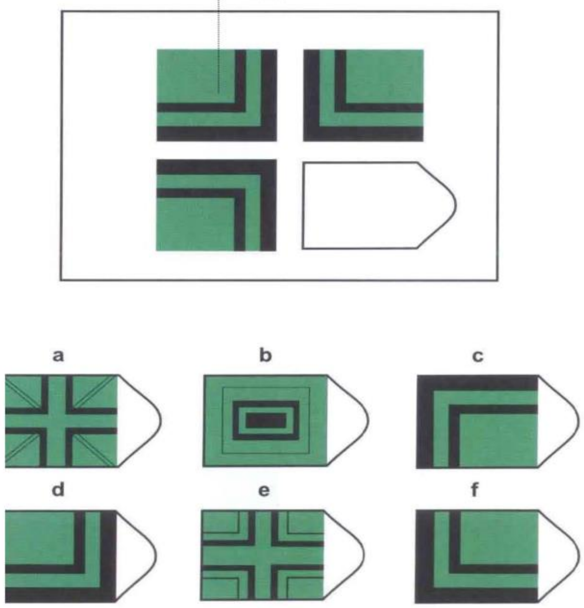
EK3



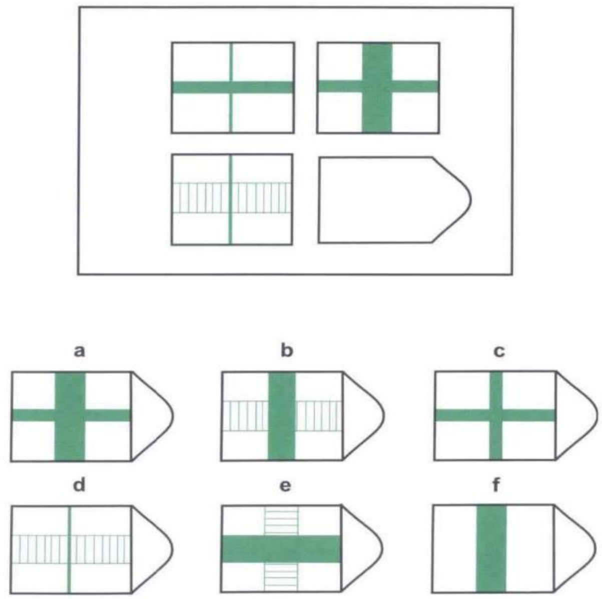
EK4



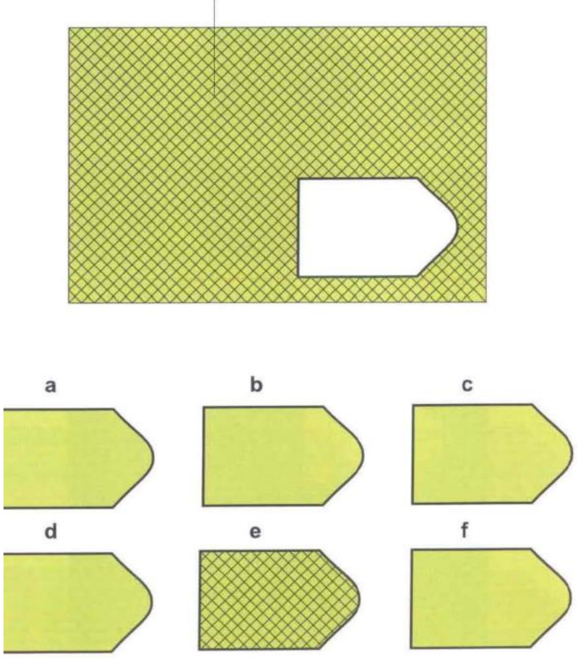
EK5



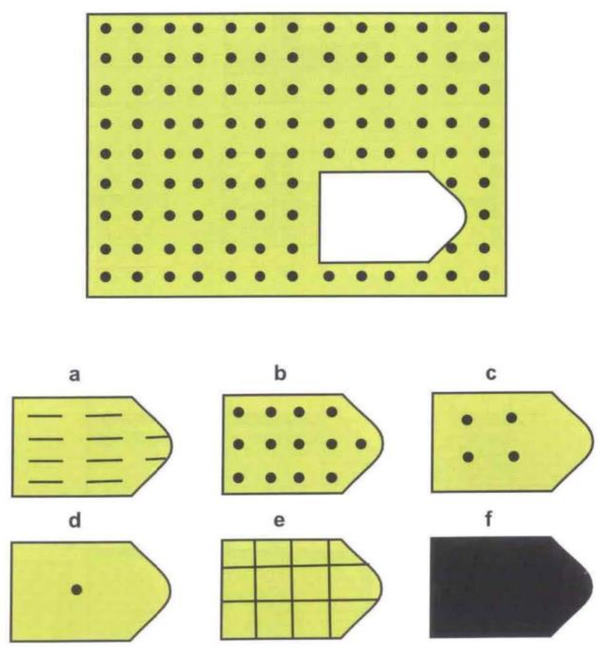
EK6



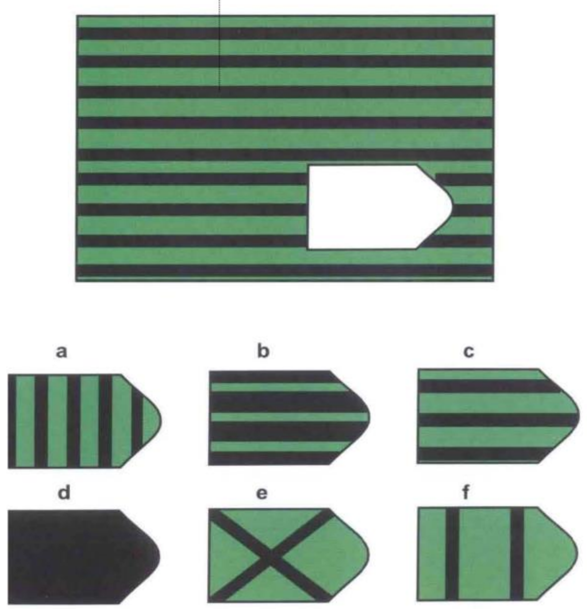
EK7



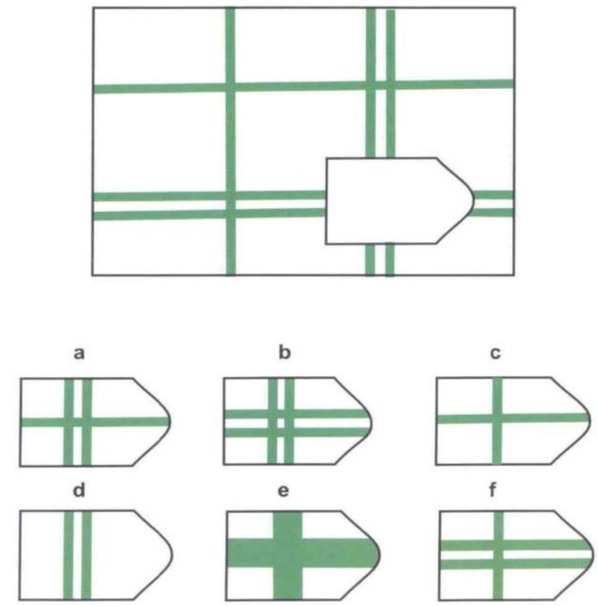
EK8



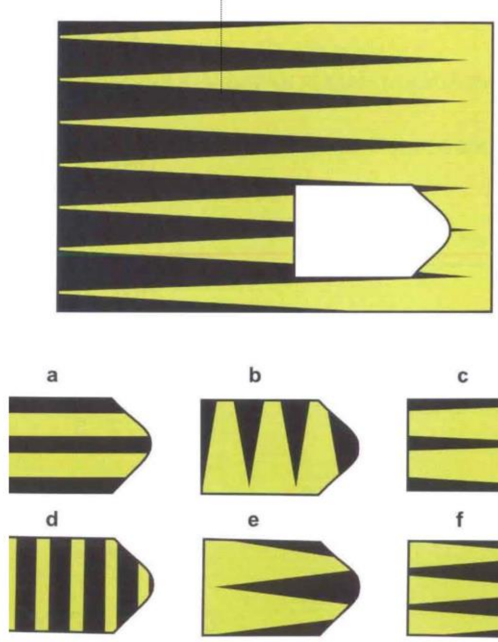
EK9



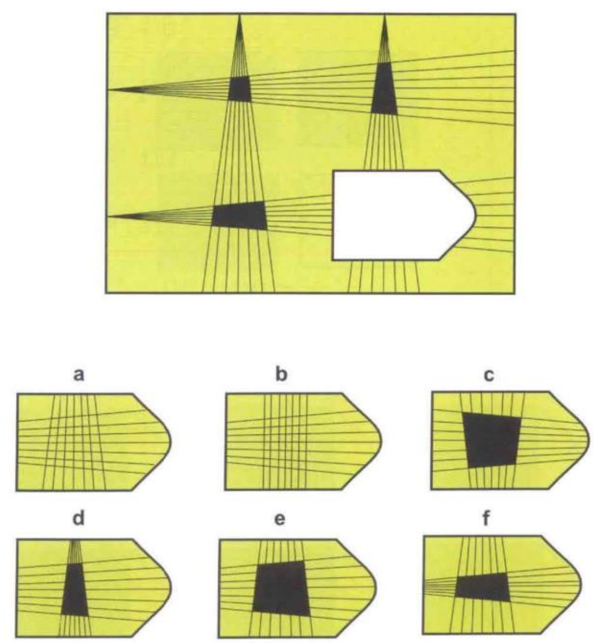
EK10



EK11



EK12



APPENDIX E

Rosenberg Self-Esteem Scale in NLSY1979:

In this appendix, information on Rosenberg Self-Esteem Scale in NLSY1979 database has been provided. The following sentence from NLSY1979 and table 27 show the question that has been asked in the 1987 and 2006 interviews:

“Now I'm going to read a list of opinions people have about themselves. After I read each statement, please tell me how much you strongly agree, agree, disagree or strongly disagree with these opinions.”

Table 27. Rosenberg Self-Esteem Scale questions in NLSY1979 database

Number	
1	I feel that I'm a person of worth, at least on equal basis with others
2	I feel that I have a number of good qualities
3	All in all, I am inclined to feel that I am a failure
4	I am able to do things as well as most other people
5	I feel I do not have much to be proud of
6	I take a positive attitude toward myself
7	On the whole, I am satisfied with myself
8	I wish I could have more respect for myself
9	I certainly feel useless at times
10	At times I think I am no good at all

Tables 28 to 31 represent data on the respondents of the Rosenberg Self-Esteem Scale questionnaire in NLSY1979. Table 28 shows the number of respondents picked each option from Rosenberg Self-Esteem Scale questions in 1987 interview.

Table 28. Data on Rosenberg Self-Esteem Scale respondents 1987

Number of the Question	Strongly Agree	Agree	Disagree	Strongly Disagree	Total
1	5780	4501	155	22	10458
2	5689	4674	82	20	10465
3	40	233	4736	5450	10459
4	4807	5451	150	40	10448
5	127	478	4696	5140	10441
6	4346	5671	380	46	10443
7	3313	6347	729	66	10455
8	299	2102	5226	2812	10439
9	163	2340	5236	2714	10453
10	82	873	5175	4328	10458

Tables 29 shows the number of respondents in the 1987 interview along with their associated Rosenberg Self-Esteem Scale scores.

Table 29. Respondents in 1987 interview along with their associated Rosenberg Self-Esteem Scale scores

Number of Respondents	Score
0	0
2	1 TO 4
4	5 TO 9
104	10 TO 14
1796	15 TO 19
4209	20 TO 24
3226	25 TO 29
999	30 TO 34

10340	
Min: 3 Max: 30	Mean: 23.37

Table 30 shows the number of respondents who picked each option from Rosenberg Self-Esteem Scale questions in 2006 interview.

Table 30. Data on Rosenberg Self-Esteem Scale respondents 2006

Number of the Question	Strongly Agree	Agree	Disagree	Strongly Disagree	Total
1	4195	3225	159	31	7610
2	4271	3285	54	15	7625
3	44	241	3538	3747	7570
4	3329	3865	365	56	7615
5	119	364	3498	3573	7554
6	3256	4032	291	37	7616
7	2483	4408	649	70	7610
8	219	1295	3628	2386	7528
9	110	1261	3685	2494	7550
10	57	485	3636	3357	7535

Tables 31 shows the number of respondents in the 2006 interview along with their associated Rosenberg Self-Esteem Scale scores.

Table 31. Respondents in 2006 interview along with their associated Rosenberg Self-Esteem Scale scores

Number of Respondents	Score
0	0
0	1 TO 4
12	5 TO 9
131	10 TO 14
1195	15 TO 19
2834	20 TO 24
2277	25 TO 29
920	30 TO 34

7369	
Min: 5 Max: 30	Mean: 23.48

APPENDIX F

Rotter Locus of Control in NLSY1979:

In this appendix, information on Rotter Locus of Control Scale in NLSY1979 database has been provided. The following sentence from NLSY1979 and tables 32 and 33 show the questions that were asked in the 2014 interview:

"I am going to read you four pairs of statements about outlooks on life. For each pair, please select *one* statement which is closer to your opinion. In addition, tell me whether the statement you select is *much closer* to your opinion or *slightly closer*. Try to consider each pair of statements separately when making your choice; do not be influenced by your previous choices."

Table 32. Rotter Locus of Control Scale questions in NLSY1979 database

Item	Question
1	Pair 1, statement A
2	Pair 1, statement B
3	Pair 2, statement A
4	Pair 2, statement B
5	Pair 3, statement A
6	Pair 3, statement B
7	Pair 4, statement A
8	Pair 4, statement B

Table 33 shows the number of respondents who picked each option related to Rotter Locus of Control Scale questions in the 2014 interview. Note that pair 1. B is asked after pair 1. A is asked. Also, pair 2. B, pair 3. B, and pair 4. B are asked after pair 2. A, pair 3. A, pair 4. A are asked, respectively.

Pair 1. B to pair 4. B ask a same question which is as follow:

"Is this statement much closer or slightly closer to your opinion?"

Table 33. Data on Rotter Locus of Control respondents 2014

Question			Number of Responses		
	Statement A	**Statement B**	**Statement A**	Statement B	Total
Pair 1	What happens to me is my own doing.	Sometimes I feel that I don't have enough control over the direction my life is taking.	5784	1186	6970
Pair 2	When I make plans, I am almost certain that I can make them work.	It is not always wise to plan too far ahead, because many things turn out to be a matter of good or bad fortune anyhow.	5004	2001	7005
Pair 3	In my case, getting what I want has little or nothing to do with luck.	Many times, we might just as well decide what to do by flipping a coin.	6070	835	6905
Pair 4	Many times, I feel that I have little influence over the things that happen to me.	It is impossible for me to believe that chance or luck plays an important role in my life.	3184	3613	6797

Table 34 shows the number of respondents picked each option from Rotter Locus of Control Scale
Pair B questions in 2014 interview.

Table 34. Data on Locus of Control respondents 2014: pair B

Question	Number of Responses		
	1. much closer	2. slightly closer	Total
Pair 1. B.	4863	2080	6943
Pair 2. B.	4794	2188	6982
Pair 3. B.	4058	2826	6884
Pair 4. B.	3184	3600	6784

Tables 35 shows the number of respondents in the 2014 interview along with their associated Rotter Locus of Control Scale scores.

Table 35. Rotter Locus of Control Scale respondents in 2014 interview along with their associated scores

Score	Number of Respondents
1 TO 4	738
5 TO 9	4522
10 TO 14	1316
15 TO 19	39
Total	6615

Min: 4 Max: 16 Mean: 7.56

APPENDIX G

The presented results of the difference-in-differences estimates in chapter 3 show the impact of eligibility for Social Security student benefits on education. Tables 36, 37, and 38 in this appendix provide the results of the estimates of the same model applying different subsets of control variables that are not provided in chapter 3.

Each of Tables 36, 37, and 38 contain four columns. The control variables in column (1) of each table include family income, black, Hispanic, father has attended college, mother has attended college, single parent, family size, age in 1988, and female. In column (2), age squared is added to the equation. This shows the sensitivity of the results to the functional form of the regression taken by age. In column (3), we have added 4 new control variables, including married, which is a binary variable that shows whether a person is married or single. Also, Nonsmsa is included in column (3). Nonsmsa sets to one if individual *i* does not live in a city, and it is zero otherwise. Another covariate in column (3) is Centrsmsa that equals to one if individual *i* lives in the central city. Zasvab is the standardized ASVAB score of individual *i*, which has been added to NLSY79 dataset in 1979. The ASVAB includes 10 tests that measure skill and knowledge in general science, arithmetic reasoning, paragraph comprehension, word knowledge, coding speed, numerical operations, mathematics knowledge, auto and shop information, electronics information, and mechanical comprehension. In the estimations provided in columns (3) and (4), a standardized ASVAB score has been added to our covariates to control for skills, knowledge, and cognitive abilities of the participants. In column (4), year of birth fixed effects and region fixed effects are added. Region of birth refers to one of the four regions in the United States: Northeast, the Midwest, the South, and the West.

Table 36. Impact of eligibility for Social Security student benefits on years of schooling by age 23

schooling by age 23	**(1)**	**(2)**	**(3)**	**(4)**
father deceased x before	0.577**	0.572**	0.561***	0.611**
	(0.230)	(0.231)	(0.234)	(0.240)
father deceased	-0.392*	-0.387*	-0.422**	0.467**
	(0.206)	(0.207)	(0.211)	(0.216)
before	0.584***	0.545***	0.528***	0.657***
	(0.156)	(0.163)	(0.163)	(0.161)
family income	Y	Y	Y	Y
black	Y	Y	Y	Y
Hispanic	Y	Y	Y	Y
father attended college	Y	Y	Y	Y
mother attended college	Y	Y	Y	Y
single parent family	Y	Y	Y	Y
family size	Y	Y	Y	Y
age88	Y	Y	Y	Y
female	Y	Y	Y	Y
age^2		Y	Y	Y
married			Y	Y
nosmsa			Y	Y
centrsmsa			Y	Y
Zasvab			Y	Y
Year of birth fixed effect				Y
Region fixed effect				Y
All covariates x before				
Number of obs.	886	886	886	875
R-squared	0.118	0.119	0.147	0.157

Note: The dependent variable is years of schooling by age 23. This is the actual number of years of schooling if the respondents in NLSY79 dataset has completed by age 23. The upper numbers in columns (1) to (4) show the coefficient of the independent variable provided in the first column (i.e. column in the left) of the table. The numbers in parentheses represent standard errors. Y means that the associated covariate is included in the estimation of the equation. All regressions are clustered at the household level. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 37. Impact of eligibility for Social Security student benefits on complete any years of college by age 23

complete college by age 23	(1)	(2)	(3)	(4)
father deceased x before	0.224***	0.224***	0.224***	0.251***
	(0.079)	(0.079)	(0.080)	(0.081)
father deceased	-0.153*	-0.154**	-0.167**	-0.192**
	(0.069)	(0.069)	(0.070)	(0.071)
before	0.135***	0.141**	0.131**	0.140***
	(0.050)	(0.058)	(0.058)	(0.058)
family income	Y	Y	Y	Y
black	Y	Y	Y	Y
Hispanic	Y	Y	Y	Y
father attended college	Y	Y	Y	Y
mother attended college	Y	Y	Y	Y
single parent family	Y	Y	Y	Y
family size	Y	Y	Y	Y
age88	Y	Y	Y	Y
female	Y	Y	Y	Y
age^2		Y	Y	Y
married			Y	Y
nosmsa			Y	Y
centrsmsa			Y	Y
Zasvab			Y	Y
Year of birth fixed effect				Y
Region fixed effect				Y
All covariates x before				
Number of obs.	895	895	895	884
R-squared	0.093	0.093	0.121	0.129

Note: The dependent variable is complete any years of college by age 23. This is a binary variable that sets to one if individual *i* has completed any years of college by age 23. It equals to zero otherwise. The upper numbers in columns (1) to (4) show the coefficient of the independent variable provided in the first column (i.e. column in the left) of the table. The numbers in parentheses represent standard errors. Y means that the associated covariate is included in the estimation of the equation. All regressions are clustered at the household level. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 38. Impact of eligibility for Social Security student benefits on complete any years of college by age 28

complete college by age 28	**(1)**	**(2)**	**(3)**	**(4)**
father deceased x before	0.316***	0.318***	0.302***	0.325***
	(0.082)	(0.082)	(0.082)	(0.083)
father deceased	-0.259*	-0.261**	-0.260**	-0.283**
	(0.072)	(0.072)	(0.072)	(0.073)
before	0.121***	0.141**	0.138***	0.144***
	(0.050)	(0.059)	(0.059)	(0.061)
family income	Y	Y	Y	Y
black	Y	Y	Y	Y
Hispanic	Y	Y	Y	Y
father attended college	Y	Y	Y	Y
mother attended college	Y	Y	Y	Y
single parent family	Y	Y	Y	Y
family size	Y	Y	Y	Y
age88	Y	Y	Y	Y
female	Y	Y	Y	Y
age^2		Y	Y	Y
married			Y	Y
nosmsa			Y	Y
centrsmsa			Y	Y
Zasvab			Y	Y
Year of birth fixed effect				Y
Region fixed effect				Y
All covariates x before				
Number of obs.	895	895	895	884
R-squared	0.114	0.115	0.139	0.150

Note: The dependent variable is complete any years of college by age 28. This is a binary variable that sets to one if individual *i* has completed any years of college by age 28. It equals to zero otherwise. The upper numbers in columns (1) to (4) show the coefficient of the independent variable provided in the first column (i.e. column in the left) of the table. The numbers in parentheses represent standard errors. Y means that the associated covariate is included in the estimation of the equation. All regressions are clustered at the household level. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

APPENDIX H

The results of the two-stage least-square estimates are provided in chapter 3. Yet, in this appendix the results of the two-stage least-square estimates are provided applying different subsets of control variables that are not provided in chapter 3. In Tables 39, 40, and 41 the instrumented variable is schooling by age 23, but in Tables 42, 43, and 44 the instrumented variable is complete any years of college by age 23. The interaction of *father deceased* and *before* is applied as our instrument in all regressions.

Table 39. Impact of education on Rosenberg Self-Esteem 1987– two-stage least-square estimations. Instrumented variable: schooling by age 23

Independent variable	(1)	(2)	(3)	Previous non-cognitive variable is control variable
Z. Rosenberg 1987	0.287** (0.113)	0.304** (0.117)	0.260** (0.118)	NO
Number of obs.	869	869	858	
Test of weak instruments: first stage F	10.784	10.037	10.919	
Z. Rosenberg 1987	0.130 (0.121)	0.148 (0.125)	0.119 (0.125)	Z. Rosenberg 1980
Number of obs.	868	868	857	
Test of weak instruments: first stage F	8.731	8.046	9.034	

Instrumented: schooling by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables in column (1) include family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age, standardized ASVAB score, and female. Column (2) includes all the covariates in column (1) as well as married, nosmsa, and centrsmsa. Column (3) includes all the covariates in column (2) and year and region fixed effects. All regressions are clustered at the household level. The numbers in parentheses represent standard errors. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 40. Impact of education on Rosenberg Self-Esteem 2006– two-stage least-square estimations. Instrumented variable: schooling by age 23

Independent variable	(1)	(2)	(3)	Previous non-cognitive variable is control variable
Z. Rosenberg 2006	0.224**	0.217**	0.131	NO
	(0.108)	(0.108)	(0.116)	
Number of obs.	640	640	631	
Test of weak instruments: first stage F	9.901	9.787	11.382	
Z. Rosenberg 2006	0.161	0.157	0.067	Z. Rosenberg 1980
	(0.117)	(0.117)	(0.128)	
Number of obs.	639	639	630	
Test of weak instruments: first stage F	8.372	8.295	9.609	

Instrumented: schooling by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables in column (1) include family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age, standardized ASVAB score, and female. Column (2) includes all the covariates in column (1) as well as married, nosmsa, and centrsmsa. Column (3) includes all the covariates in column (2) and year and region fixed effects. All regressions are clustered at the household level. The numbers in parentheses represent standard errors. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 41. Impact of education on Rotter Locus of Control 2014– two-stage least-square estimations. Instrumented variable: schooling by age 23

Independent variable	(1)	(2)	(3)	Previous non-cognitive variable is control variable
Z. Rotter 2014	0.259*	0.242	0.224	NO
	(0.155)	(0.151)	(0.137)	
Number of obs.	557	557	549	
Test of weak instruments: first stage F	15.246	15.136	15.301	
Z. Rotter 2014	0.247	0.232	0.220	Z. Rotter 1979
	(0.158)	(0.156)	(0.141)	
Number of obs.	554	554	546	
Test of weak instruments: first stage F	15.520	15.342	15.087	

Instrumented: schooling by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables in column (1) include family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age, standardized ASVAB score, and female. Column (2) includes all the covariates in column (1) as well as married, nosmsa, and centrsmsa. Column (3) includes all the covariates in column (2) and year and region fixed effects. All regressions are clustered at the household level. The numbers in parentheses represent standard errors. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 42. Impact of education on Rosenberg Self-Esteem 1987– two-stage least-square estimations. Instrumented variable: complete any years of college by age 23

Independent variable	(1)	(2)	(3)	Previous non-cognitive variable is control variable
Z. Rosenberg 1987	0.905**	0.972**	0.820**	NO
	(0.388)	(0.403)	(0.405)	
Number of obs.	876	876	865	
Test of weak instruments: first stage F	9.859	9.364	7.943	
Z. Rosenberg 1987	0.354	0.418	0.330	Z. Rosenberg 1980
	(0.425)	(0.446)	(0.444)	
Number of obs.	875	875	864	
Test of weak instruments: first stage F	7.548	7.083	6.306	

Instrumented: complete any years of college by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables in column (1) include family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age, standardized ASVAB score, and female. Column (2) includes all the covariates in column (1) as well as married, nosmsa, and centrsmsa. Column (3) includes all the covariates in column (2) and year and region fixed effects. All regressions are clustered at the household level. The numbers in parentheses represent standard errors. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 43. Impact of education on Rosenberg Self-Esteem 2006– two-stage least-square estimations. Instrumented variable: complete any years of college by age 23

Independent variable	(1)	(2)	(3)	Previous non-cognitive variable is control variable
Z. Rosenberg 2006	0.824**	0.800**	0.467	NO
	(0.382)	(0.386)	(0.356)	
Number of obs.	646	646	637	
Test of weak instruments: first stage F	8.841	8.882	9.913	
Z. Rosenberg 2006	0.588	0.569	0.252	Z. Rosenberg 1980
	(0.414)	(0.419)	(0.391)	
Number of obs.	645	645	636	
Test of weak instruments: first stage F	7.076	7.111	8.164	

Instrumented: complete any years of college by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables in column (1) include family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age, standardized ASVAB score, and female. Column (2) includes all the covariates in column (1) as well as married, nosmsa, and centrsmsa. Column (3) includes all the covariates in column (2) and year and region fixed effects. All regressions are clustered at the household level. The numbers in parentheses represent standard errors. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

Table 44. Impact of education Rotter Locus of Control 2014– two-stage least-square estimations. Instrumented variable: complete any years of college by age 23

Independent variable	(1)	(2)	(3)	Previous non-cognitive variable is control variable
Z. Rotter 2014	0.850*	0.794*	0.674	NO
	(0.471)	(0.465)	(0.414)	
Number of obs.	562	562	554	
Test of weak instruments: first stage F	11.746	12.372	12.765	
Z. Rotter 2014	0.812*	0.761	0.660	Z. Rotter 1979
	(0.491)	(0.489)	(0.432)	
Number of obs.	559	559	551	
Test of weak instruments: first stage F	11.206	11.807	12.489	

Instrumented: complete any years of college by age 23
Instrument: interaction of *father deceased* and *before*
Test of weak instrument Ho: Instruments are weak
Control variables in column (1) include family income, black, Hispanic, father attended college, mother attended college, single parent family, family size, age, standardized ASVAB score, and female. Column (2) includes all the covariates in column (1) as well as married, nosmsa, and centrsmsa. Column (3) includes all the covariates in column (2) and year and region fixed effects. All regressions are clustered at the household level. The numbers in parentheses represent standard errors. *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.

BIBLIOGRAPHY

Acemoglu, D., Finkelstein, A., & Notowidigdo, M. J. (2013). Income and health spending: Evidence from oil price shocks. *Review of Economics and Statistics*, *95*(4), 1079-1095.

Akresh, R., Halim, D., & Kleemans, M. (2018). *Long-term and intergenerational effects of education: Evidence from school construction in Indonesia* (No. w25265). National Bureau of Economic Research.

Arcidiacono, P., Bayer, P., & Hizmo, A. (2010). Beyond signaling and human capital: Education and the revelation of ability. *American Economic Journal: Applied Economics*, *2*(4), 76-104.

Aydın, L., & Acar, M. (2011). Economic impact of oil price shocks on the Turkish economy in the coming decades: A dynamic CGE analysis. *Energy Policy*, *39*(3), 1722-1731.

Bachman, J. G., O'Malley, P. M., & Johnston, J. (1978). Adolescence to adulthood--change and stability in the lives of young men.

Baumeister, R. F., Campbell, J. D., Krueger, J. I., & Vohs, K. D. (2003). Does high self-esteem cause better performance, interpersonal success, happiness, or healthier lifestyles?. *Psychological science in the public interest*, *4*(1), 1-44.

Becker, G. S. (1992). Human capital and the economy. *Proceedings of the American philosophical society*, *136*(1), 85-92.

Becker, G. S., Philipson, T. J., & Soares, R. R. (2005). The quantity and quality of life and the evolution of world inequality. *The American Economic Review*, *95*(1), 277-291.

Belsky, J. (1990). *The psychology of aging: Theory, research, and interventions*. Brooks/Cole Pub. Co.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of political economy*, *75*(4, Part 1), 352-365.

Bergmann, P. (2019). Oil price shocks and GDP growth: Do energy shares amplify causal effects?. *Energy Economics*, *80*, 1010-1040.

Bietenbeck, J., Ericsson, S., & Wamalwa, F. M. (2019). Preschool attendance, schooling, and cognitive skills in East Africa. *Economics of Education Review*, *73*, 101909.

Blair, C., Gamson, D., Thorne, S., & Baker, D. (2005). Rising mean IQ: Cognitive demand of mathematics education for young children, population exposure to formal schooling, and the neurobiology of the prefrontal cortex. *Intelligence*, *33*(1), 93-106.

Bloom, D., & Canning, D. (2007). Commentary: The Preston Curve 30 years on: Still sparking fires. *International Journal of Epidemiology*, *36*(3), 498-499.

Boden, J. M., Fergusson, D. M., & Horwood, L. J. (2007). Self-esteem and violence: Testing links between adolescent self-esteem and later hostility and violent behavior. *Social Psychiatry and Psychiatric Epidemiology*, *42*(11), 881-891.

Boden, J. M., Fergusson, D. M., & Horwood, L. J. (2008). Does adolescent self-esteem predict later life outcomes? A test of the causal role of self-esteem. *Development and psychopathology*, *20*(1), 319-339.

Boissiere, M., Knight, J. B., & Sabot, R. H. (1985). Earnings, schooling, ability, and cognitive skills. *The American Economic Review*, *75*(5), 1016-1030.

Borgonovi, F., & Pokropek, A. (2016). Education and self-reported health: Evidence from 23 countries on the role of years of schooling, cognitive skills and social capital. *PloS one*, *11*(2), e0149716.

Bouchard, T. J., & Loehlin, J. C. (2001). Genes, evolution, and personality. *Behavior genetics*, *31*(3), 243-273.

Bowles, S., Gintis, H., & Osborne, M. (2001). The determinants of earnings: A behavioral approach. *Journal of economic literature*, *39*(4), 1137-1176.

Bowles, T. (1999). Focusing on time orientation to explain adolescent selfconcept and academic achievement. *Journal of Applied Health Behavior*, *1*, 1-8.

Braveman, P. A., Cubbin, C., Egerter, S., Williams, D. R., & Pamuk, E. (2010). Socioeconomic disparities in health in the United States: what the patterns tell us. *American journal of public health*, *100*(S1), S186-S196.

Brickman, P., & Bulman, R. J. (1977). Pleasure and pain in social comparison. *Social comparison processes: Theoretical and empirical perspectives*, *149*, 186.

Brollo, F., Nannicini, T., Perotti, R., & Tabellini, G. (2010). The political resource curse. *American Economic Review*, 103(5):1759-96.

Butler, R. (1989). Mastery versus ability appraisal: A developmental study of children's observations of peers' work. *Child Development*, 1350-1361.

Cahan, S., & Cohen, N. (1989). Age versus schooling effects on intelligence development. *Child development*, 1239-1249.

Caliendo, M., Cobb-Clark, D. A., & Uhlendorff, A. (2015). Locus of control and job search strategies. *Review of Economics and Statistics*, *97*(1), 88-103.

Card, D., & Krueger, A. B. (1992). Does school quality matter? Returns to education and the characteristics of public schools in the United States. *Journal of political Economy*, *100*(1), 1-40.

Card, D., & Krueger, A. B. (1994). *Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania* (No. w4509). National Bureau of Economic Research.

Card, D., & Lemieux, T. (1998). Earnings, Education and the Canadian GI Bill. *Na-tional Bureau of Economic Research (Cam-bridge, MA) Working Paper*, (6718).

Carlsson, M., Dahl, G. B., Öckert, B., & Rooth, D. O. (2015). The effect of schooling on cognitive skills. *Review of Economics and Statistics*, *97*(3), 533-547.

Carlsson, M., Dahl, G. B., Öckert, B., & Rooth, D. O. (2015). The effect of schooling on cognitive skills. *Review of Economics and Statistics*, *97*(3), 533-547.

Cascio, E. U., & Lewis, E. G. (2006). Schooling and the armed forces qualifying test evidence from school-entry laws. *Journal of Human resources*, *41*(2), 294-318.

Cascio, E. U., & Lewis, E. G. (2006). Schooling and the armed forces qualifying test evidence from school-entry laws. *Journal of Human resources*, *41*(2), 294-318.

Caselli, F., & Cunningham, T. (2009). Leader behaviour and the natural resource curse. *Oxford Economic Papers*, 61(4), 628-650.

Caselli, F., & Michaels, G. (2009a). Resource abundance, development, and living standards: evidence from oil discoveries in Brazil. *NBER Working Paper,* 15550.

Caselli, F., & Michaels, G. (2009b). Do oil windfalls improve living standards? Evidence from Brazil (No. w15550). *National Bureau of Economic Research*.

Casner-Lotto, J., & Barrington, L. (2006). *Are they really ready to work? Employers' perspectives on the basic knowledge and applied skills of new entrants to the 21st century US workforce*. Partnership for 21st Century Skills. 1 Massachusetts Avenue NW Suite 700, Washington, DC 20001.

Castro, J. F., & Rolleston, C. (2018). The contribution of early childhood and schools to cognitive gaps: New evidence from Peru. *Economics of Education Review*, *64*, 144-164.

Cattell, R. B. (1971). Abilities: Their structure, growth, and action.

Ceci, S. J. (1991). How much does schooling influence general intelligence and its cognitive components? A reassessment of the evidence. *Developmental psychology*, *27*(5), 703.

Checchi, D., & De Paola, M. (2018). The effect of multigrade classes on cognitive and non-cognitive skills. Causal evidence exploiting minimum class size rules in Italy☆. *Economics of Education Review*, *67*, 235-253.

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., ... & Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. *Jama*, *315*(16), 1750-1766.

Christopher Auld, M., & Sidhu, N. (2005). Schooling, cognitive ability and health. *Health economics*, *14*(10), 1019-1034.

CIA report, Shah of Iran Culprit in High Oil Prices, CIA-RDP91-00561R000100070048-2.

Cliffordson, C., & Gustafsson, J. E. (2008). Effects of age and schooling on intellectual performance: Estimates obtained from analysis of continuous variation in age and length of schooling. *Intelligence*, *36*(2), 143-152.

Cliffordson, C., & Gustafsson, J. E. (2008). Effects of age and schooling on intellectual performance: Estimates obtained from analysis of continuous variation in age and length of schooling. *Intelligence*, *36*(2), 143-152.

Cobb-Clark, D. A. (2015). Locus of control and the labor market. *IZA Journal of Labor Economics, 4*(1), 3.

Cotton, S. M., Kiely, P. M., Crewther, D. P., Thomson, B., Laycock, R., & Crewther, S. G. (2005). A normative and reliability study for the Raven's Coloured Progressive Matrices for primary school aged children from Victoria, Australia. *Personality and individual differences*, *39*(3), 647-659.

Cristia, J. P., DeLeire, A. H., Iams, H., Kile, J., Manchester, J., Meyerson, N., ... & Walker, L. (2007). *The empirical relationship between lifetime earnings and mortality*. Congressional Budget Office.

Crocker, J., & Wolfe, C. T. (2001). Contingencies of self-worth. *Psychological review*, *108*(3), 593.

Crocker, J., Sommers, S. R., & Luhtanen, R. K. (2002). Hopes dashed and dreams fulfilled: Contingencies of self-worth and graduate school admissions. *Personality and Social Psychology Bulletin*, *28*(9), 1275-1286.

Cross, J., & Nguyen, B. H. (2017). The relationship between global oil price shocks and China's output: A time-varying analysis. *Energy economics*, *62*, 79-91.

Cunado, J., & de Gracia, F. P. (2014). Oil price shocks and stock market returns: Evidence for some European countries. *Energy Economics*, *42*, 365-377.

Cunado, J., Jo, S., & de Gracia, F. P. (2015). Macroeconomic impacts of oil price shocks in Asian economies. *Energy Policy*, *86*, 867-879.

Cutler, D., Lleras-Muney, A., & Deaton, A. (2006). The Determinants of Mortality. *20*(3), 97-120.

Dahmann, S. C. (2017). How does education improve cognitive skills? Instructional time versus timing of instruction. *Labour Economics*, *47*, 35-47.

Daroesman, Ruth. "Finance of Education Part 1." *Bulletin of Indonesian Economic Studies* 7.3 (1971): 61-95. Web.

de Araujo, P., & Lagos, S. (2013). Self-esteem, education, and wages revisited. *Journal of Economic Psychology*, *34*, 120-132.

Deary, I. J., Strand, S., Smith, P., & Fernandes, C. (2007). Intelligence and educational achievement. *Intelligence*, *35*(1), 13-21.

Deaton, A. (2006). The great escape: A review of Robert Fogel's the escape from hunger and premature death, 1700–2100. *Journal of Economic Literature*, *44*(1), 106-114.

Dee, T. S., & West, M. R. (2011). The non-cognitive returns to class size. *Educational Evaluation and Policy Analysis*, *33*(1), 23-46.

Deke, J., & Haimson, J. (2006). Valuing Student Competencies: Which Ones Predict Postsecondary Educational Attainment and Earnings, and for Whom? Final Report. *Mathematica Policy Research, Inc.*

Demeny, P. (1965). Investment Allocation and Population Growth. *Demography, 2*, 203-232.

Drago, F. (2011). Self-esteem and earnings. *Journal of Economic Psychology*, *32*(3), 480-488.

Duflo, E. (2001). Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. *American economic review*, *91*(4), 795-813.

Duggan, J. E., Greenlees, J. S., & Gillingham, R. (2008). *Mortality and lifetime income: evidence from US social security records* (No. 7-15). International Monetary Fund.

Dutton, E., & Lynn, R. (2013). A negative Flynn effect in Finland, 1997–2009. *Intelligence*, *41*(6), 817-820.

Dutton, E., & Lynn, R. (2015). A negative Flynn Effect in France, 1999 to 2008–9. *Intelligence*, *51*, 67-70.

Dynarski, S. M. (2003). Does aid matter? Measuring the effect of student aid on college attendance and completion. *American Economic Review*, *93*(1), 279-288.

Farzanegan, M. R., & Markwardt, G. (2009). The effects of oil price shocks on the Iranian economy. *Energy Economics*, *31*(1), 134-151.

Flynn, J. R. (1987). Massive IQ gains in 14 nations: What IQ tests really measure. *Psychological bulletin*, *101*(2), 171.

Flynn, J. R. (2018). Reflections about intelligence over 40 years. *Intelligence*, *70*, 73-83.

Flynn, J. R., & Flynn, J. R. (2012). *Are we getting smarter?: Rising IQ in the twenty-first century*. Cambridge University Press.

Fogel, R. W. (2004). *The escape from hunger and premature death, 1700-2100: Europe, America, and the Third World* (Vol. 38). Cambridge University Press.

Fortin, N. M. (2008). The gender wage gap among young adults in the united states the importance of money versus people. *Journal of Human Resources*, *43*(4), 884-918.

Fox, M. C., & Charness, N. (2010). How to gain eleven IQ points in ten minutes: Thinking aloud improves Raven's Matrices performance in older adults. *Aging, Neuropsychology, and cognition*, *17*(2), 191-204.

Gao, L., Kim, H., & Saba, R. (2014). How do oil price shocks affect consumer prices?. *Energy Economics*, *45*, 313-323.

Garcia, E. (2016). The need to address non-cognitive skills in the education policy agenda. In *Non-cognitive skills and factors in educational attainment* (pp. 31-64). Brill Sense.

Geary, David C. (2005). *The Origin of Mind : Evolution of Brain, Cognition, and General Intelligence*. 1st ed. Washington, DC: American Psychological Association. Print.

Gintis, H. (1971). Education, technology, and the characteristics of worker productivity. *The American Economic Review*, *61*(2), 266-279.

Graetz, G. (2017). Human Capital, Signaling, and Employer Learning. What Insights Do We Gain from Regression Discontinuity Designs.

Grigoli, F., Herman, A., & Swiston, A. (2019). A crude shock: Explaining the short-run impact of the 2014–16 oil price decline across exporters. *Energy Economics*, *78*, 481-493.

Gustafsson, J. E. (2016). Lasting effects of quality of schooling: Evidence from PISA and PIAAC. *Intelligence*, *57*, 66-72.

Gustafsson, J. E. (2016). Lasting effects of quality of schooling: Evidence from PISA and PIAAC. *Intelligence*, *57*, 66-72.

Gylfason, T. (2001). Natural resources, education, and economic development. *European economic review*, 45(4), 847-859.

Gylfason, T., Herbertsson, T., & Zoega, G. (1999). A MIXED BLESSING. *Macroeconomic Dynamics*, *3*(02), 204-225.

Hansen, K. T., Heckman, J. J., & Mullen, K. J. (2004). The effect of schooling and ability on achievement test scores. *Journal of econometrics*, *121*(1-2), 39-98.

Hansen, K. T., Heckman, J. J., & Mullen, K. J. (2004). The effect of schooling and ability on achievement test scores. *Journal of econometrics*, *121*(1-2), 39-98.

Harvey, J. M. (1971). Locus of control shift in administrators. *Perceptual and Motor Skills*, *33*(3), 980-982.

Hasanov, F. (2013). Dutch disease and the Azerbaijan economy. *Communist and Post-Communist Studies*, *46*(4), 463-480.

Heckman, J. J., & Kautz, T. (2013). *Fostering and measuring skills: Interventions that improve character and cognition* (No. w19656). National Bureau of Economic Research.

Heckman, J. J., & Rubinstein, Y. (2001). The importance of noncognitive skills: Lessons from the GED testing program. *American Economic Review*, *91*(2), 145-149.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor economics*, *24*(3), 411-482.

Heckman, J., & Vytlacil, E. (2001). Identifying the role of cognitive ability in explaining the level of and change in the return to schooling. *Review of Economics and Statistics*, *83*(1), 1-12.

Heckman, J., Pinto, R., & Savelyev, P. (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review*, *103*(6), 2052-86.

Heineck, G., & Anger, S. (2010). The returns to cognitive abilities and personality traits in Germany. *Labour economics*, *17*(3), 535-546.

Herrera, A. M., Karaki, M. B., & Rangaraju, S. K. (2019). Oil price shocks and US economic activity. *Energy policy*, *129*, 89-99.

Herrnstein, R. J., & Murray, C. (1994). The bell curve: The reshaping of American life by differences in intelligence. *New York: Free*.

Ioannidis, C., & Ka, K. (2018). The impact of oil price shocks on the term structure of interest rates. *Energy Economics*, *72*, 601-620.

Iwayemi, A., & Fowowe, B. (2011). Impact of oil price shocks on selected macroeconomic variables in Nigeria. *Energy policy*, *39*(2), 603-612.

Jacob, B. A. (2002). Where the boys aren't: Non-cognitive skills, returns to school and the gender gap in higher education. *Economics of Education review*, *21*(6), 589-598.

Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Perrig, W. J. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences*, *105*(19), 6829-6833.

Jagannathan, R., Camasso, M. J., & Delacalle, M. (2019). Promoting cognitive and soft skills acquisition in a disadvantaged public school system: Evidence from the Nurture thru Nature randomized experiment. *Economics of Education Review*, *70*, 173-191.

Jimenez-Rodriguez, R. (2008). The impact of oil price shocks: Evidence from the industries of six OECD countries. *Energy Economics*, *30*(6), 3095-3108.

Jo, S., Karnizova, L., & Reza, A. (2018). Industry effects of oil price shocks: A re-examination. *Energy Economics*.

Jonsson, B., Waling, M., Olafsdottir, A. S., Lagström, H., Wergedahl, H., Olsson, C., ... & Hörnell, A. (2017). The effect of schooling on basic cognition in selected Nordic Countries. *Europe's journal of psychology*, *13*(4), 645.

Ju, K., Su, B., Zhou, D., Wu, J., & Liu, L. (2016). Macroeconomic performance of oil price shocks: Outlier evidence from nineteen major oil-related countries/regions. *Energy Economics*, *60*, 325-332.

Kang, W., Ratti, R. A., & Yoon, K. H. (2014). The impact of oil price shocks on US bond market returns. *Energy Economics*, *44*, 248-258.

Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., & Borghans, L. (2014). Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success. OECD Education Working Papers 110, OECD Publishing.

Kim, W. J., Hammoudeh, S., Hyun, J. S., & Gupta, R. (2017). Oil price shocks and China's economy: Reactions of the monetary policy to oil price shocks. *Energy Economics*, *62*, 61-69.

Kitagawa, E., & Hauser, Philip M. (1973). *Differential Mortality in the United States: A Study in Socioeconomic Epidemiology*.

Kuhn, P., & Weinberger, C. (2005). Leadership skills and wages. *Journal of Labor Economics*, *23*(3), 395-436.

Kuster, F., Orth, U., & Meier, L. L. (2013). High self-esteem prospectively predicts better work conditions and outcomes. *Social Psychological and Personality Science*, *4*(6), 668-675.

Lee, C. C., & Lee, C. C. (2019). Oil price shocks and Chinese banking performance: Do country risks matter?. *Energy Economics*, *77*, 46-53.

Lee, C. C., Lee, C. C., & Ning, S. L. (2017). Dynamic relationship of oil price shocks and country risks. *Energy Economics*, *66*, 571-581.

Leite, C. A., & Weidmann, J. (1999). Does mother nature corrupt? Natural resources, corruption, and economic growth. Natural Resources, Corruption, and Economic Growth (June 1999). *IMF Working Paper*, (99/85).

Lorusso, M., & Pieroni, L. (2018). Causes and consequences of oil price shocks on the UK economy. *Economic Modelling*, *72*, 223-236.

Lundberg, S. (2017). Non-cognitive skills as human capital. In *Education, Skills, and Technical Change: Implications for Future US GDP Growth*. University of Chicago Press.

Mackenbach, J. P., & Looman, C. W. (2013). Life expectancy and national income in Europe, 1900-2008: an update of Preston's analysis. *International journal of epidemiology*, *42*(4), 1100-1110.

Mackenbach, J. P., Stirbu, I., Roskam, A. J. R., Schaap, M. M., Menvielle, G., Leinsalu, M., & Kunst, A. E. (2008). Socioeconomic inequalities in health in 22 European countries. *New England Journal of Medicine*, *358*(23), 2468-2481.

Marshall, S. L., Parker, P. D., Ciarrochi, J., & Heaven, P. C. (2014). Is self-esteem a cause or consequence of social support? A 4-year longitudinal study. *Child Development*, *85*(3), 1275-1291.

Michaels, G. (2011). The long-term consequences of resource-based specialisation. *The Economic Journal*, *121*(551), 31-57.

Moshiri, S., & Moghaddam, M. B. (2018). The effects of oil price shocks in a federation; The case of interregional trade and labour migration. *Energy Economics*, *75*, 206-221.

Murnane, R. J., Willett, J. B., Braatz, M. J., & Duhaldeborde, Y. (2001). Do different dimensions of male high school students' skills predict labor market success a decade later? Evidence from the NLSY. *Economics of Education Review*, *20*(4), 311-320.

Nasir, M. A., Naidoo, L., Shahbaz, M., & Amoo, N. (2018). Implications of oil prices shocks for the major emerging economies: A comparative analysis of BRICS. *Energy Economics*, *76*, 76-88.

Neal, D. A., & Johnson, W. R. (1996). The role of premarket factors in black-white wage differences. *Journal of political Economy*, *104*(5), 869-895.

Neisser, U., Boodoo, G., Bouchard Jr, T. J., Boykin, A. W., Brody, N., Ceci, S. J., ... & Urbina, S. (1996). Intelligence: Knowns and unknowns. *American psychologist*, *51*(2), 77.

Nusair, S. A. (2016). The effects of oil price shocks on the economies of the Gulf Co-operation Council countries: Nonlinear analysis. *Energy Policy*, *91*, 256-267.

Nusair, S. A., & Olson, D. (2019). The effects of oil price shocks on Asian exchange rates: Evidence from quantile regression analysis. *Energy Economics*, *78*, 44-63.

Oladosu, G. A., Leiby, P. N., Bowman, D. C., Uría-Martínez, R., & Johnson, M. M. (2018). Impacts of oil price shocks on the United States economy: A meta-analysis of the oil price elasticity of GDP for net oil-importing economies. *Energy policy*, *115*, 523-544.

Oomes, N., & Kalcheva, K. (2007). *Diagnosing Dutch disease: does Russia have the symptoms?* (Vol. 7). International Monetary Fund.

Orth, U., & Robins, R. W. (2014). The development of self-esteem. *Current Directions in Psychological Science*, *23*(5), 381-387.

Orth, U., Robins, R. W., & Widaman, K. F. (2012). Life-span development of self-esteem and its effects on important life outcomes. *Journal of personality and social psychology*, *102*(6), 1271.

Orth, U., Robins, R. W., Trzesniewski, K. H., Maes, J., & Schmitt, M. (2009). Low self-esteem is a risk factor for depressive symptoms from young adulthood to old age. *Journal of abnormal psychology*, *118*(3), 472.

Papavlassopulos, N., & Keppler, D. (2011). Life expectancy as an objective factor of a subjective well-being. *Social indicators research*, *104*(3), 475-505.

Papyrakis, E., & Gerlagh, R. (2007). Resource abundance and economic growth in the United States. European Economic Review, 51(4), 1011-1039.

Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the US and 13 European countries. *Energy economics*, *30*(5), 2587-2608.

Pascarella, E. T., & Terenzini, P. T. (1991). *How college affects students: Findings and insights from twenty years of research*. Jossey-Bass Inc., Publishers, PO Box 44305, San Francisco, CA 94144-4305 (ISBN-1-55542-304-3).

Pietschnig, J., & Gittler, G. (2015). A reversal of the Flynn effect for spatial perception in German-speaking countries: Evidence from a cross-temporal IRT-based meta-analysis (1977–2014). *Intelligence*, *53*, 145-153.

Pomerantz, E. M., Ruble, D. N., Frey, K. S., & Greulich, F. (1995). Meeting goals and confronting conflict: Children's changing perceptions of social comparison. *Child Development*, *66*(3), 723-738.

Preston, S. (2007). The changing relation between mortality and level of economic development. *International Journal of Epidemiology*, *36*(3), 484-490.

Preston, S. H. (1975). The changing relation between mortality and level of economic development. *Population studies*, *29*(2), 231-248.

Raven, J. C. (1936). Mental tests used in genetic studies: The performance of related individuals on tests mainly educative and mainly reproductive. *Unpublished master's thesis, University of London*.

Rodgers III, W. M., & Spriggs, W. E. (1996). What does the AFQT really measure: Race, wages, schooling and the AFQT score. *The Review of Black Political Economy*, *24*(4), 13-46.

Rohde, T. E., & Thompson, L. A. (2007). Predicting academic achievement with cognitive ability. *Intelligence*, *35*(1), 83-92.

Rosenberg, M., Schooler, C., & Schoenbach, C. (1989). Self-esteem and adolescent problems: Modeling reciprocal effects. *American sociological review*, 1004-1018.

Ross, M. L. (2001). Does oil hinder democracy?. *World politics*, 53(3), 325-361.

Ruble, D. N., & Frey, K. S. (1991). Changing patterns of comparative behavior as skills are acquired: A functional model of self-evaluation.

Sachs, J. D., & Warner, A. M. (1995). Natural resource abundance and economic growth (No. w5398). *National Bureau of Economic Research*.

Sala-i-Martin, X., & Subramanian, Arvind. (2013). Addressing the natural resource curse an illustration from Nigeria. *Journal of African Economies*,*22*(4), 570-615.

Scholtens, B., & Yurtsever, C. (2012). Oil price shocks and European industries. *Energy Economics*, *34*(4), 1187-1195.

Skaalvik, E. M., & Hagtvet, K. A. (1990). Academic achievement and self-concept: An analysis of causal predominance in a developmental perspective. *Journal of personality and Social Psychology*, *58*(2), 292.

Smith, B. (2015). The resource curse exorcised: Evidence from a panel of countries. *Journal of development economics*, 116, 57-73.

Staff, R. T., Hogan, M. J., & Whalley, L. J. (2014). Aging trajectories of fluid intelligence in late life: The influence of age, practice and childhood IQ on Raven's Progressive Matrices. *Intelligence*, *47*, 194-201.

Stelzl, I., Merz, F., Ehlers, T., & Remer, H. (1995). The effect of schooling on the development of fluid and cristallized intelligence: A quasi-experimental study. *Intelligence*, *21*(3), 279-296.

Stevenson, H. W., Chen, C., & Booth, J. (1990). Influences of schooling and urban-rural residence on gender differences in cognitive abilities and academic achievement. *Sex Roles*, *23*(9-10), 535-551.

Stolnitz, G. (1965). Recent mortality trends in Latin America, Asia and Africa. *Population Studies, 19*(2), 117-138.

Tach, L. M., & Farkas, G. (2006). Learning-related behaviors, cognitive skills, and ability grouping when schooling begins. *Social Science Research*, *35*(4), 1048-1079.

Taylor, S. E., & Lobel, M. (1989). Social comparison activity under threat: Downward evaluation and upward contacts. *Psychological review*, *96*(4), 569.

Tchatoka, F. D., Masson, V., & Parry, S. (2018). Linkages between oil price shocks and stock returns revisited. *Energy Economics*.

te Nijenhuis, J., van Vianen, A. E., & van der Flier, H. (2007). Score gains on g-loaded tests: No g. *Intelligence*, *35*(3), 283-300.

Tornell, A., & Lane, P. R. (1999). The voracity effect. american economic review, 22-46.

Trzesniewski, K. H., Donnellan, M. B., Moffitt, T. E., Robins, R. W., Poulton, R., & Caspi, A. (2006). Low self-esteem during adolescence predicts poor health, criminal behavior, and limited economic prospects during adulthood. *Developmental psychology*, *42*(2), 381.

Tsai, C. L. (2015). How do US stock returns respond differently to oil price shocks pre-crisis, within the financial crisis, and post-crisis?. *Energy Economics*, *50*, 47-62.

Van der Ploeg, F. (2011). Natural resources: Curse or blessing?. Journal of Economic Literature, 366-420.

Velasco, A. (1997). A model of endogenous fiscal deficits and delayed fiscal reforms (No. w6336). *National Bureau of Economic Research.*

Vicente, P. C. (2010). Does oil corrupt? Evidence from a natural experiment in West Africa. *Journal of Development Economics*, 92(1), 28-38.

Waddell, G. R. (2006). Labor‐Market Consequences of Poor Attitude and Low Self‐Esteem in Youth. *Economic Inquiry*, *44*(1), 69-97.

Waldron, H. (2013). Mortality differentials by lifetime earnings decile: Implications for evaluations of proposed social security law changes. *Social Security Bulletin*, *73*(1), 1-37.

Welland, J. D. (1978). Cognitive abilities, schooling and earnings: the question of functional form. *The Review of Economics and Statistics*, 622-627.

Winship, C., & Korenman, S. (1997). Does staying in school make you smarter? The effect of education on IQ in The Bell Curve. In *Intelligence, genes, and success* (pp. 215-234). Springer, New York, NY.

Wolfle, L. M., & List, J. H. (2004). Temporal stability in the effects of college attendance on locus of control, 1972–1992. *Structural Equation Modeling*, *11*(2), 244-260.

Wolfle, L. M., & Robertshaw, D. (1982). Effects of college attendance on locus of control. *Journal of Personality and social psychology*, *43*(4), 802.

Zhang, C., & Qu, X. (2015). The effect of global oil price shocks on China's agricultural commodities. *Energy Economics*, *51*, 354-364.

Zhang, C., & Tu, X. (2016). The effect of global oil price shocks on China's metal markets. *Energy Policy*, *90*, 131-139.

Zhao, L., Zhang, X., Wang, S., & Xu, S. (2016). The effects of oil price shocks on output and inflation in China. *Energy Economics*, *53*, 101-110.